

An Introduction to (Hybrid) Probabilistic Logic Programming

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IJCAI - Hybrid Reasoning 2015



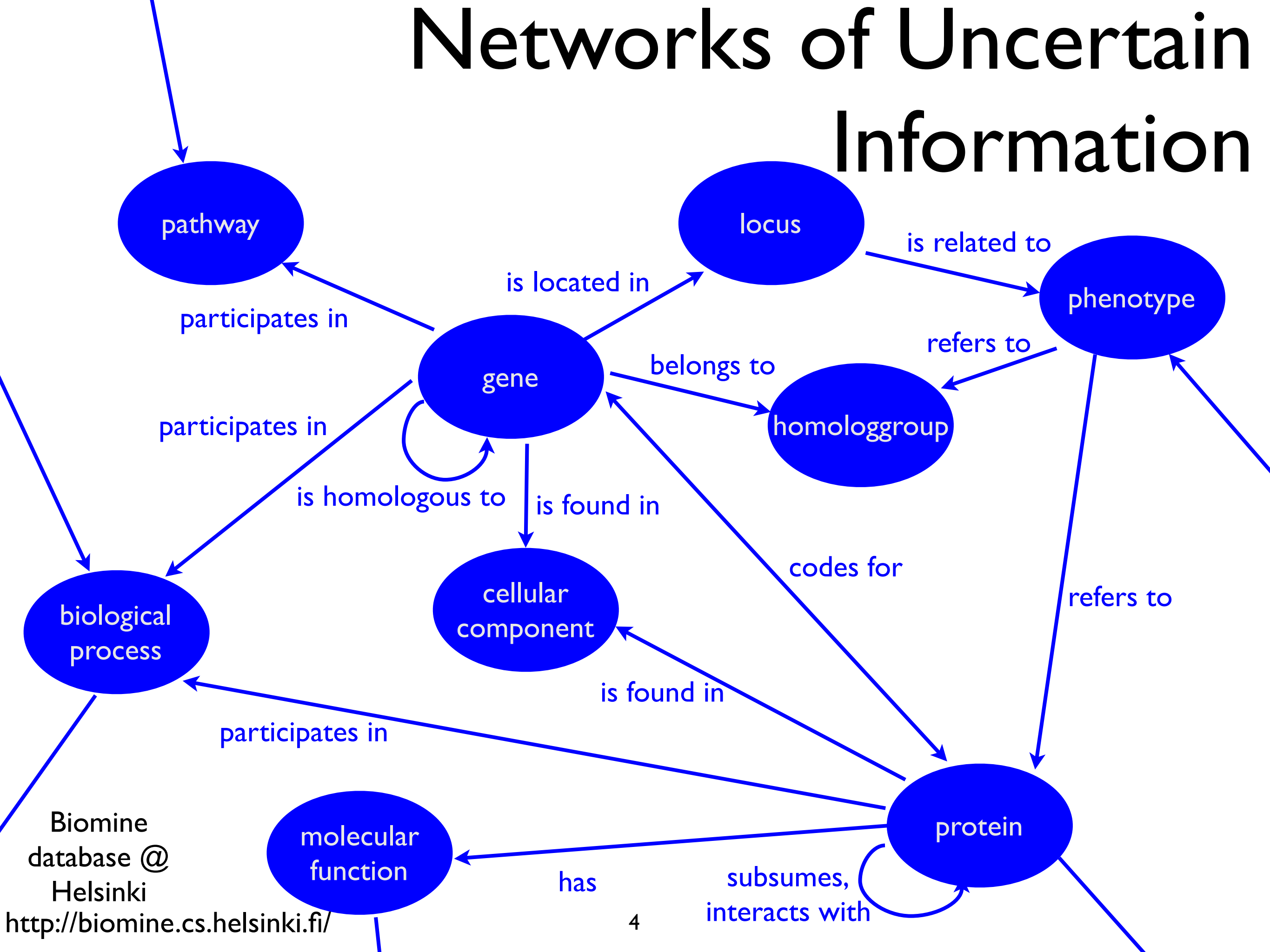
KU LEUVEN

Overview

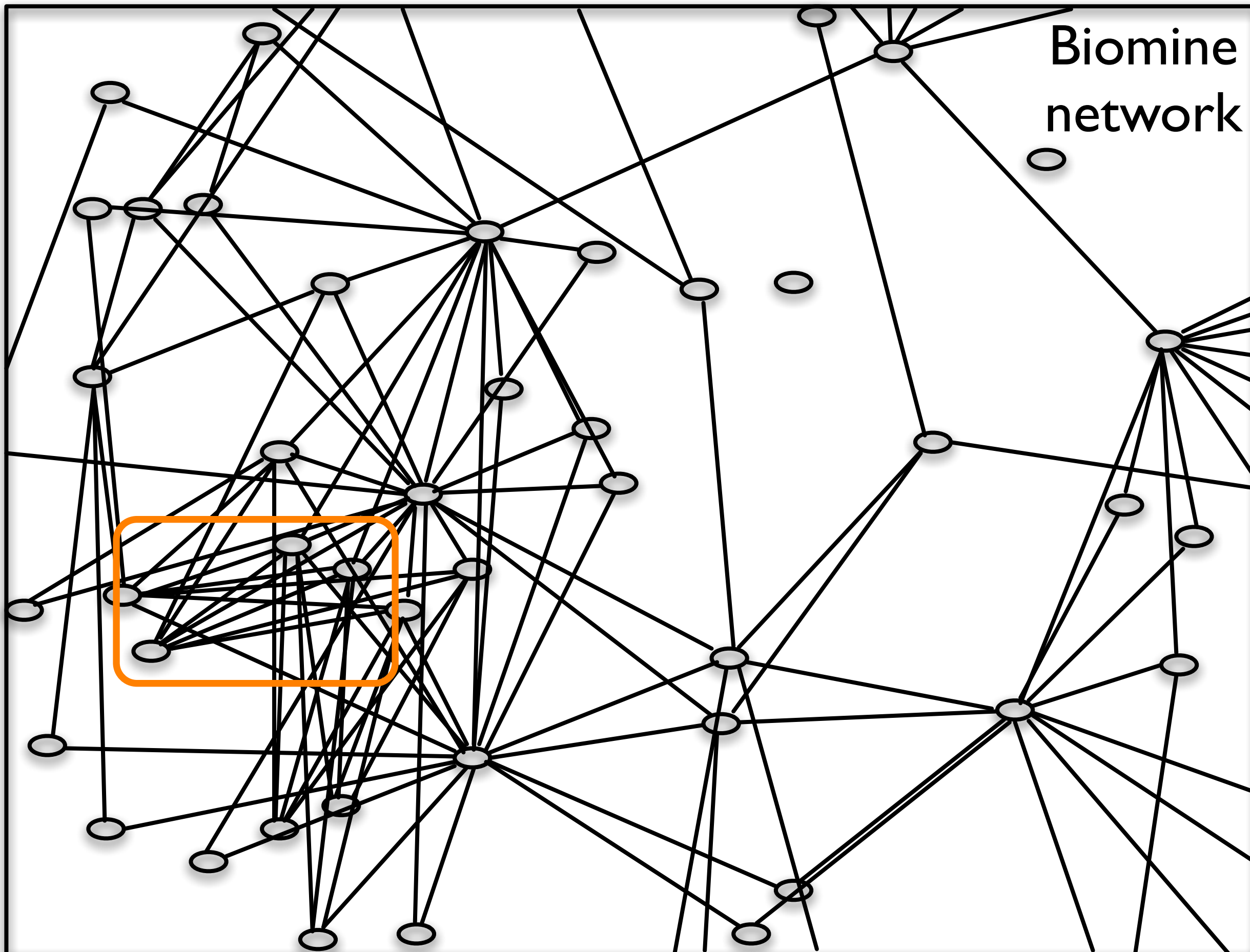
- Part I :An introduction to Prob. Logic Programming and the relation to alternative frameworks
- Part II : Inference
- Part III: Learning
- Part IV: Dynamics & Continuous distributions for Relational Tracking (in Robotics)
- *Focus on ProbLog line of research at KU Leuven*

PART I: Intro to PLP

Networks of Uncertain Information



Biomine
network



Notch receptor processing

Biological Process

GO:GO:0007220

Biological Process

Notch receptor processing
Biological Process
GO:GO:0007220

-participates_in
0.220

-participates_in
0.197

-is_found_in
0.259

is_homologous_to
0.530

-participates_in
0.219

-participates_in
0.207

found_in
0.271

-participates_in
0.229

participates_in
0.192

integral to nuclear inner
CellularComponent
GO:GO:0005639

presenilin 2

Gene

EntrezGene:81751

presenilin 2
Gene
EntrezGene:81751

Gene

Phenetic

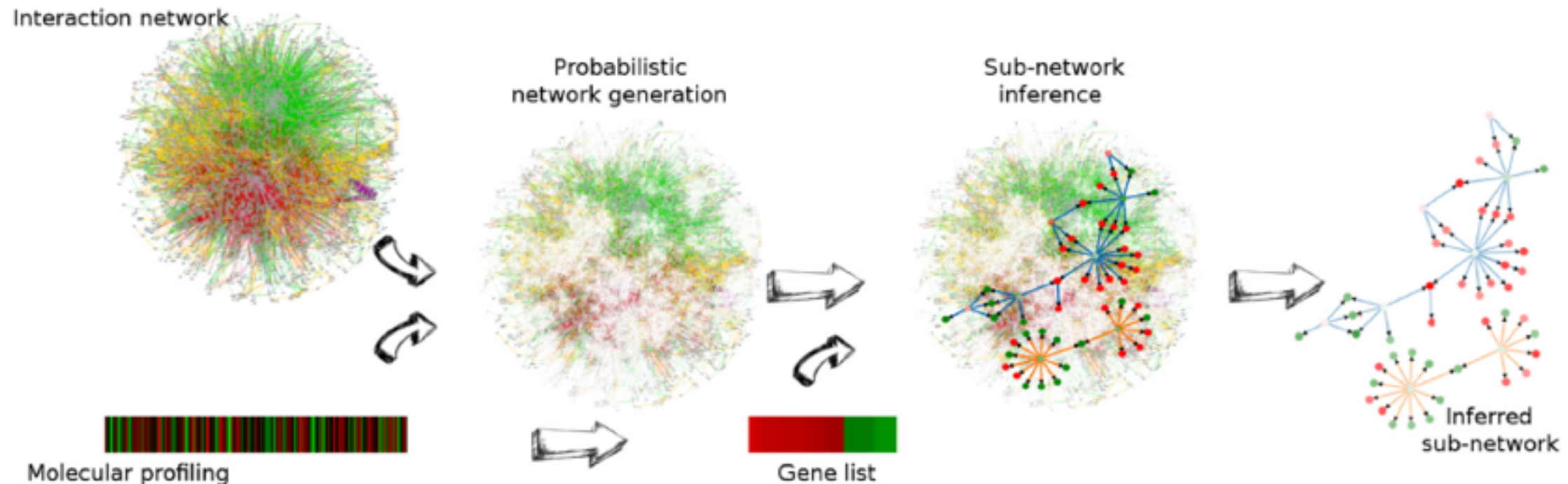























Figure 1. Overview of PheNetic, a web service for network-based interpretation of ‘omics’ data. The web service uses as input a genome wide interaction network for the organism of interest, a user generated molecular profiling data set and a gene list derived from these data. Interaction networks for a wide variety of organisms are readily available from the web server. Using the uploaded user-generated molecular data the interaction network is converted into a probabilistic network: edges receive a probability proportional to the levels measured for the terminal nodes in the molecular profiling data set. This probabilistic interaction network is used to infer the sub-network that best links the genes from the gene list. The inferred sub-network provides a trade-off between linking as many genes as possible from the gene list and selecting the least number of edges.

- Causes: Mutations
 - All related to similar phenotype
- Effects: Differentially expressed genes
 - 27 000 cause effect pairs
- Interaction network:
 - 3063 nodes
 - Genes
 - Proteins
 - 16794 edges
 - Molecular interactions
 - Uncertain
- Goal: connect causes to effects through common subnetwork
 - = Find mechanism
- Techniques:
 - DTProbLog
 - Approximate inference

Can we find the mechanism connecting causes to effects?

Example: Information Extraction

Recently-Learned Facts Refresh

instance	iteration	date learned	confidence
<u>kelly andrews</u> is a <u>female</u>	826	29-mar-2014	98.7  
<u>investment next year</u> is an <u>economic sector</u>	829	10-apr-2014	95.3  
<u>shibenik</u> is a <u>geopolitical entity</u> that is an organization	829	10-apr-2014	97.2  
<u>quality web design work</u> is a <u>character trait</u>	826	29-mar-2014	91.0  
<u>mercedes benz cls by carlsson</u> is an <u>automobile manufacturer</u>	829	10-apr-2014	95.2  
<u>social work</u> is an academic program <u>at the university rutgers university</u>	827	02-apr-2014	93.8  
<u>dante wrote</u> the book <u>the divine comedy</u>	826	29-mar-2014	93.8  
<u>willie aames</u> was <u>born in</u> the city <u>los angeles</u>	831	16-apr-2014	100.0  
<u>kitt peak</u> is a mountain <u>in the state or province arizona</u>	831	16-apr-2014	96.9  
<u>greenwich</u> is a park <u>in the city london</u>	831	16-apr-2014	100.0  

↑
instances for many
different relations

↑
degree of certainty

Graphs & Randomness

ProbLog, Phenetic, Prism, ICL, Probabilistic Databases, ...

- all based on a “random graph” model

Stochastic Logic Programs, ProPPR, PCFGs, ...

- based on a “random walk” model
- connected to PageRank
- not the subject of this talk !

Probabilistic Logic Programming

Distribution Semantics [Sato, ICLP 95]:
probabilistic choices + logic program
→ distribution over possible worlds

e.g., PRISM, ICL, ProbLog, LPADs, CP-logic, ...

multi-valued
switches

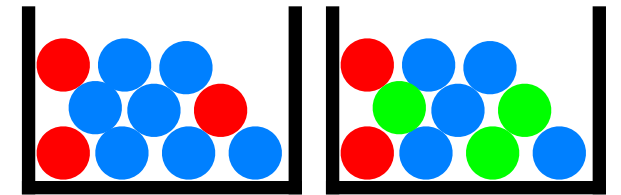
probabilistic
facts

probabilistic
alternatives

annotated
disjunctions

causal-
probabilistic
laws

ProbLog by example:



A bit of gambling

- toss (biased) coin & draw ball from each urn
- win if (heads and a red ball) or (two balls of same color)

```
0.4 :: heads.
```

probabilistic fact: heads is true with probability 0.4 and false with 0.6)
annotated disjunction: first ball is red with probability 0.3 and blue with 0.7

```
0.3 :: col(1,red) ; 0.7 :: col(1,blue) <- true.
```

```
0.2 :: col(2,red) ; 0.3 :: col(2,green) ;
```

```
0.5 :: col(2,blue) <- true.
```

annotated disjunction: second ball is red with probability 0.2, green with 0.3, and blue with 0.5

```
win :- heads, col(1,red).  
win :- col(1,C) , col(2,C) .
```

logical rule encoding background knowledge
consequences

Questions

```
0.4 :: heads.
```

```
0.3 :: col(1,red) ; 0.7 :: col(1,blue) <- true.
```

```
0.2 :: col(2,red) ; 0.3 :: col(2,green) ; 0.5 :: col(2,blue) <- true.
```

```
win :- heads, col(_,red).
```

```
win :- col(1,C), col(2,C).
```

marginal probability

- Probability of **win**

conditional probability

- Probability of **win** given **col(2,green)**?

- Most probable world where **win** is true?

MPE inference

Possible Worlds

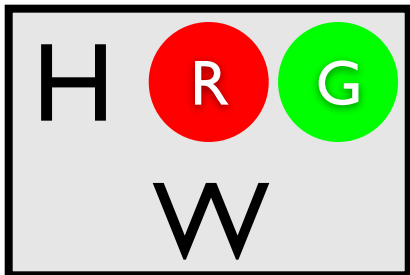
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0.4 :: heads.
```

```
0.3 :: col(1,red); 0.7 :: col(1,blue) <- true.
```

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0.2 :: col(2,red); 0.3 :: col(2,green); 0.5 :: col(2,blue) <- true.
```

```
win :- heads, col(_,red).  
win :- col(1,C), col(2,C).
```

$0.4 \times 0.3 \times 0.3$



Possible Worlds

```
0.4 :: heads.
```

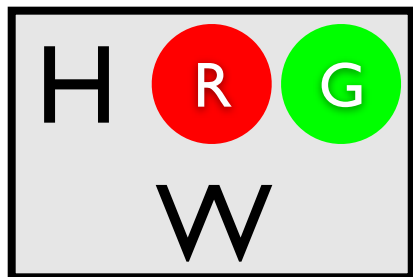
```
0.3 :: col(1,red); 0.7 :: col(1,blue) <- true.
```

```
0.2 :: col(2,red); 0.3 :: col(2,green); 0.5 :: col(2,blue) <- true.
```

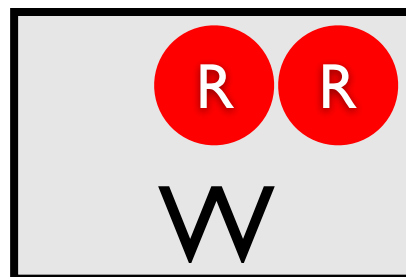
```
win :- heads, col(_,red).
```

```
win :- col(1,C), col(2,C).
```

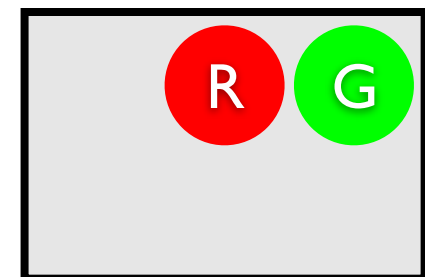
$0.4 \times 0.3 \times 0.3$



$(1-0.4) \times 0.3 \times 0.2$

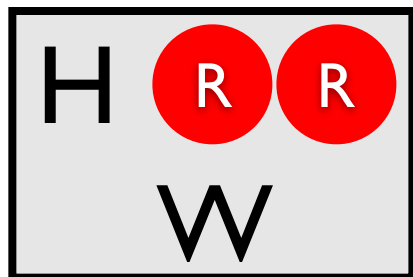


$(1-0.4) \times 0.3 \times 0.3$

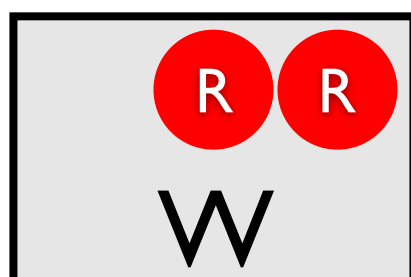


All Possible Worlds

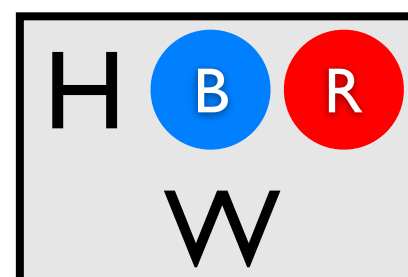
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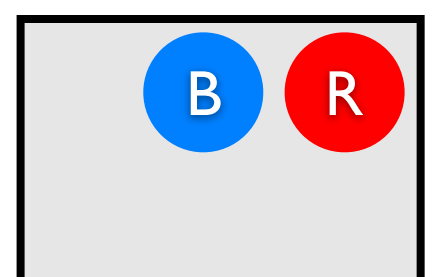
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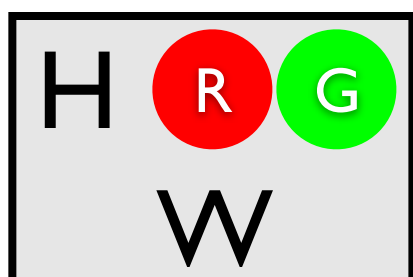
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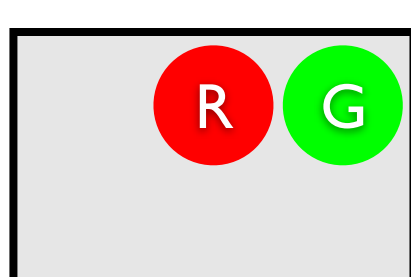
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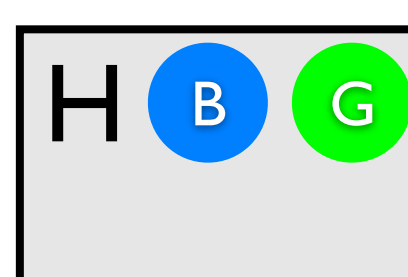
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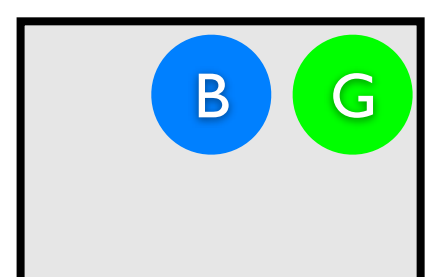
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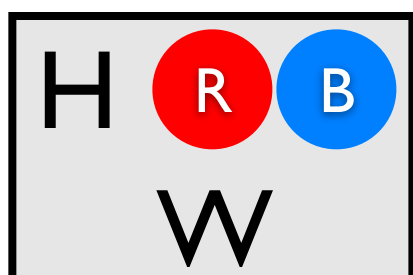
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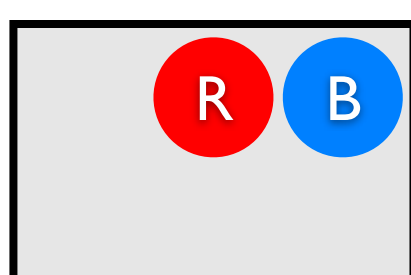
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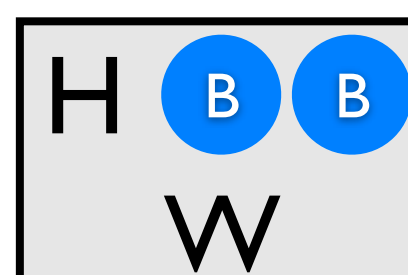
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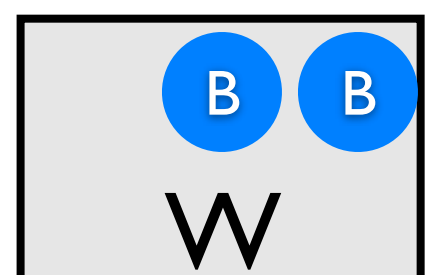
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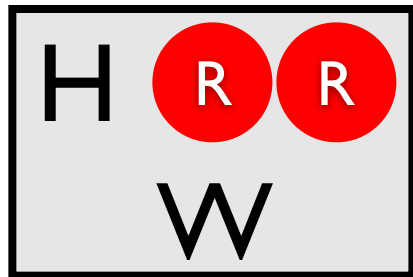
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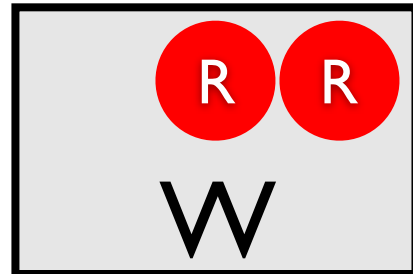
$$P(\text{win}) = \sum = 0.562$$

Marginal
Probability

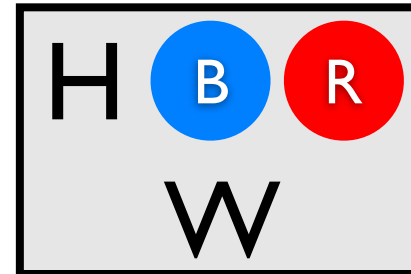
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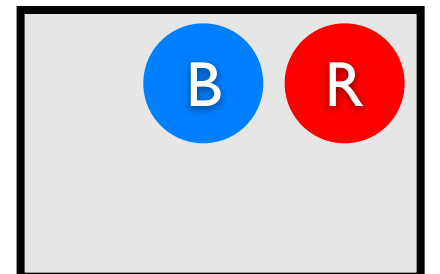
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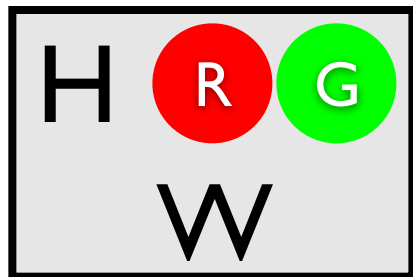
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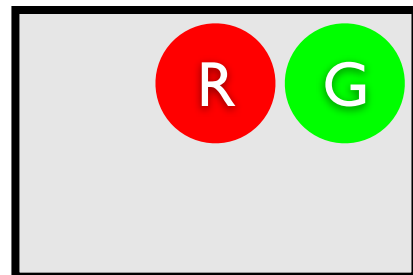
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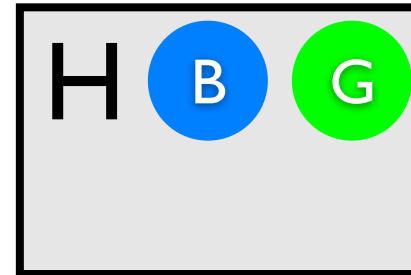
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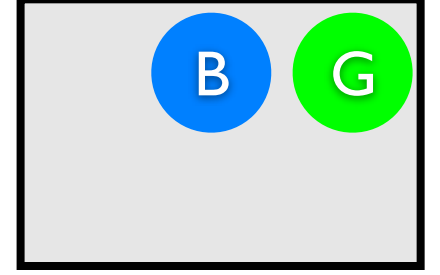
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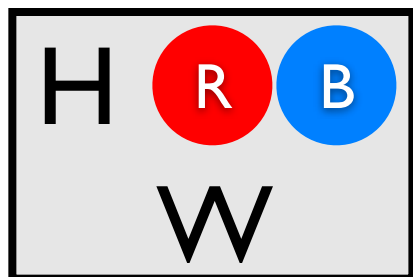
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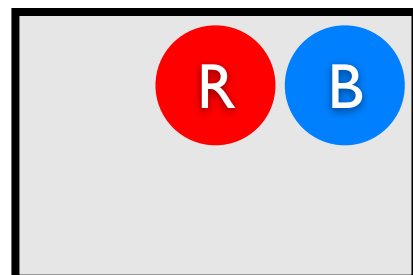
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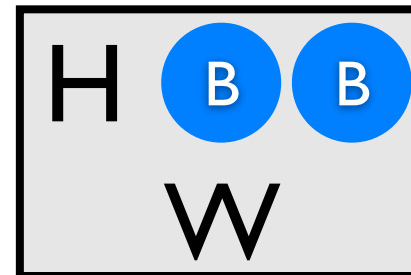
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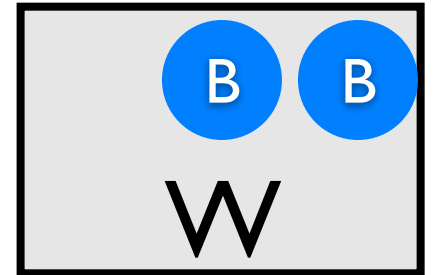
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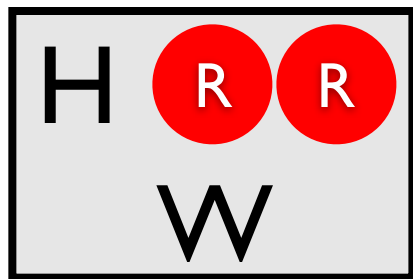


$$P(\text{win}|\text{col}(2,\text{green})) = \frac{?}{\Sigma}$$

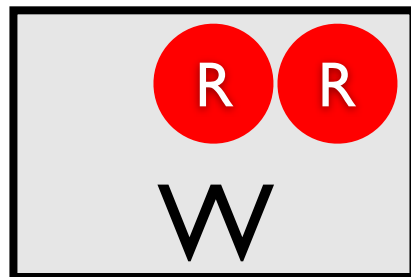
$$= \frac{P(\text{win} \wedge \text{col}(2,\text{green}))}{P(\text{col}(2,\text{green}))}$$

Conditional Probability

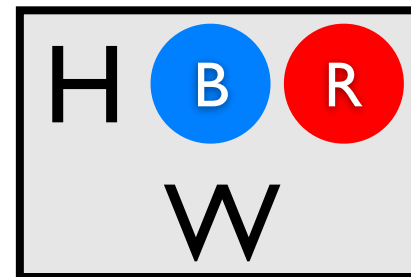
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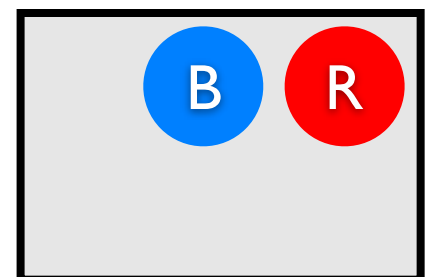
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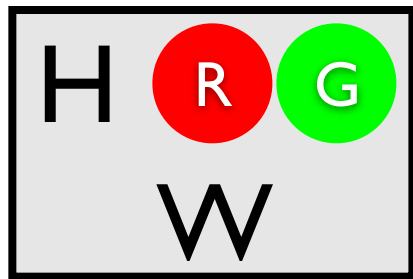
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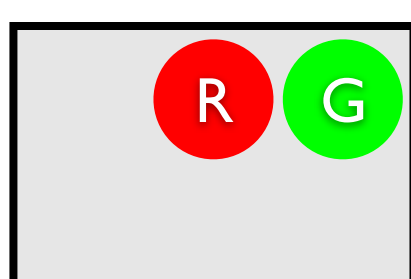
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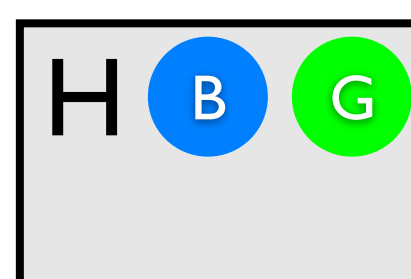
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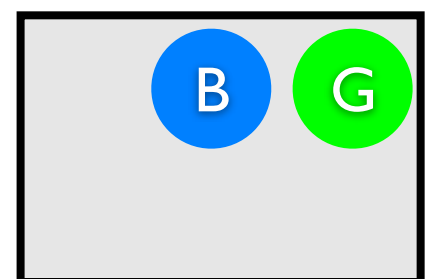
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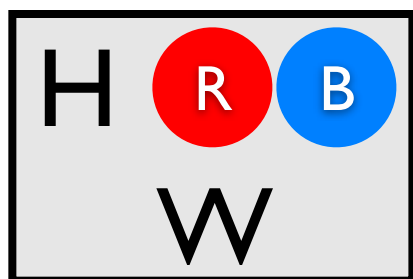
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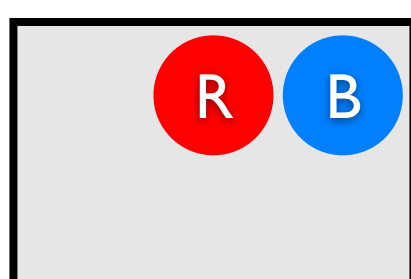
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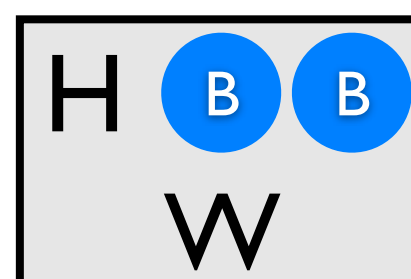
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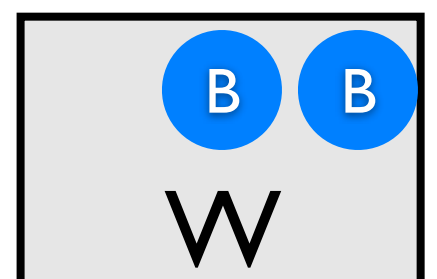
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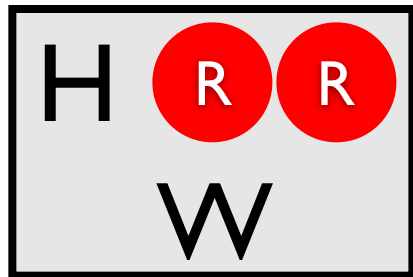
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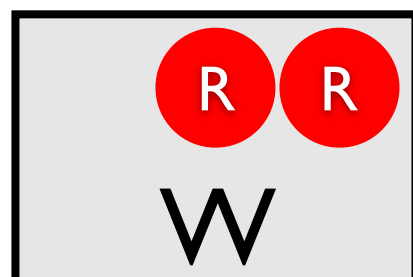
Most likely world where `win` is true?

MPE Inference

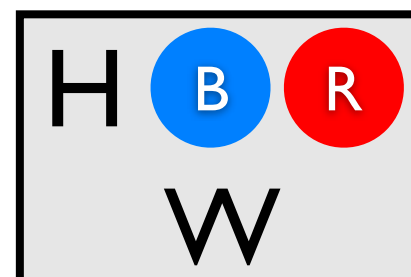
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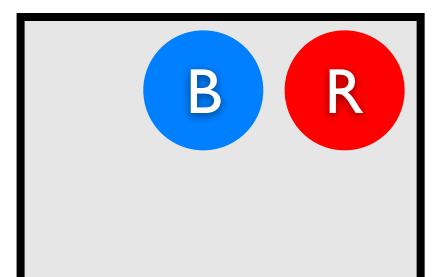
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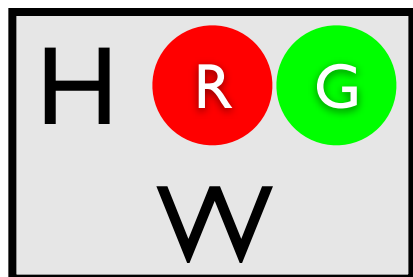
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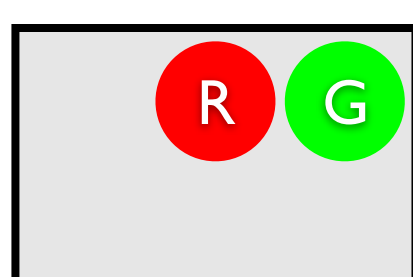
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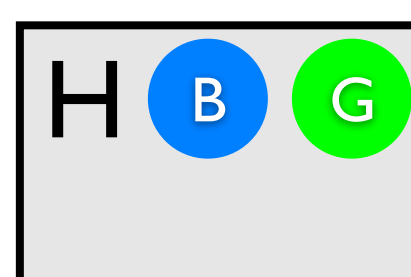
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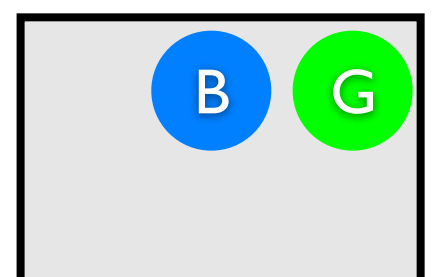
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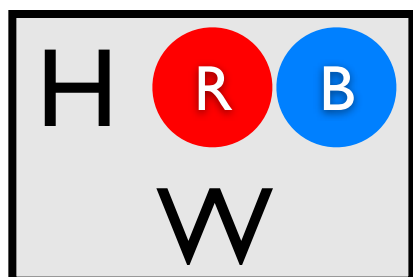
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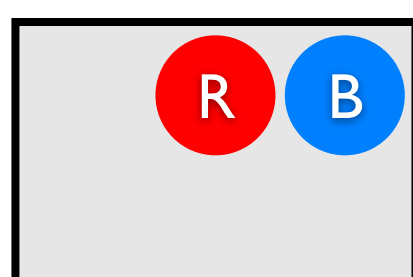
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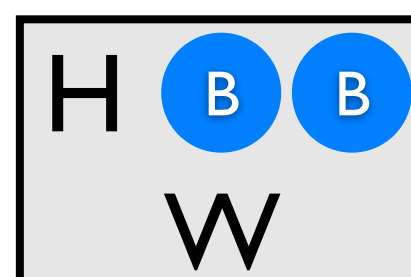
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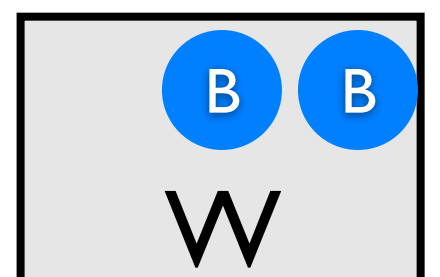
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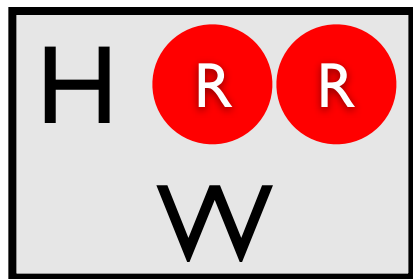
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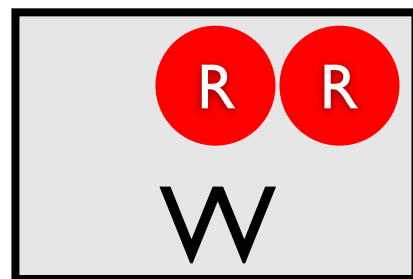
Most likely world where `col(2, blue)` is false?

MPE Inference

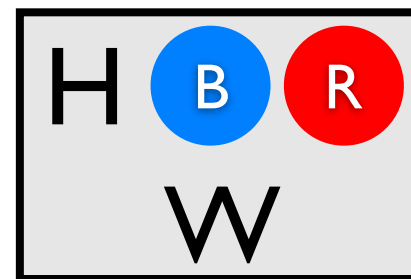
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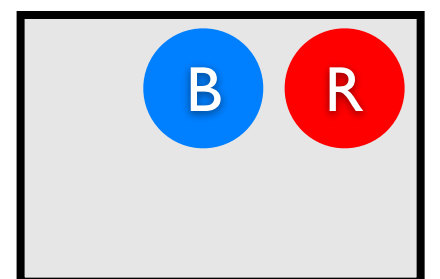
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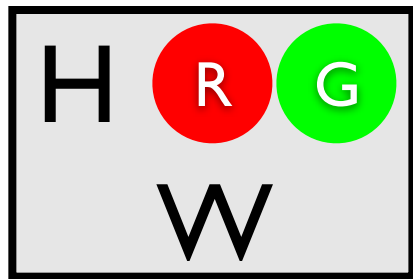
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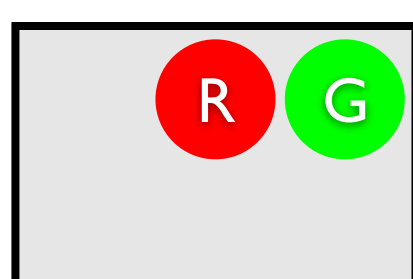
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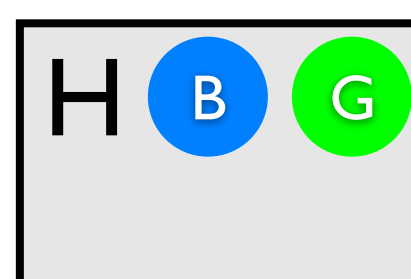
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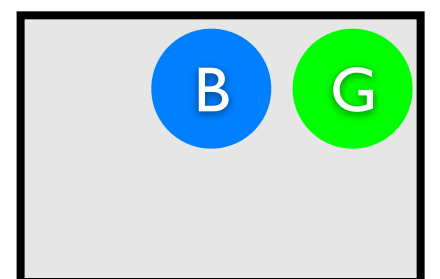
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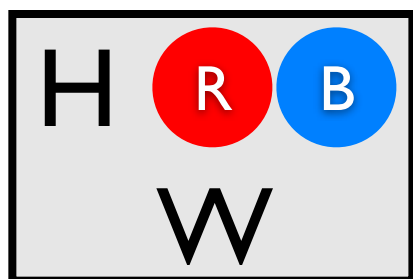
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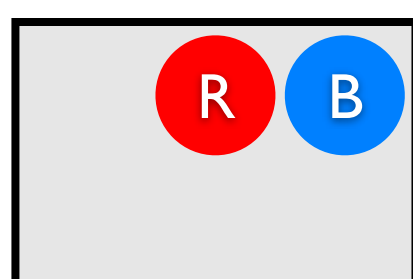
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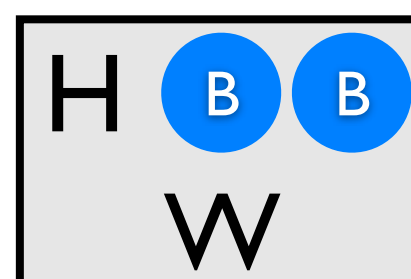
0.060



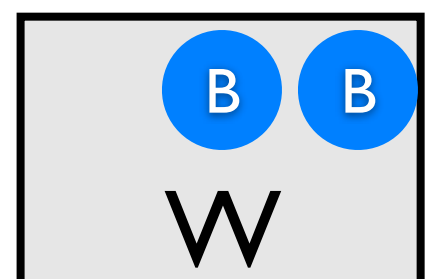
0.090



0.140



0.210



Distribution Semantics

(with probabilistic facts)

[Sato, ICLP 95]

query

sum over possible worlds
where Q is true

$$P(Q) = \sum_{F \cup R \models Q} \prod_{f \in F} p(f) \prod_{f \notin F} 1 - p(f)$$

subset of
probabilistic
facts

Prolog
rules

probability of
possible world

cProbLog: constraints on possible worlds

```
weight(skis,6).
weight(boots,4).
weight(helmet,3).
weight(gloves,2).
```

```
P::pack(Item) :-
    weight(Item,Weight),
    P is 1.0/Weight.
```

```
excess(Limit) :- ...
```

```
not excess(10).
pack(helmet) v pack(boots).
```

constraints
as FOL formulas
treat as evidence

distribution
normalized distribution
over all possible
over restricted set of
possible worlds

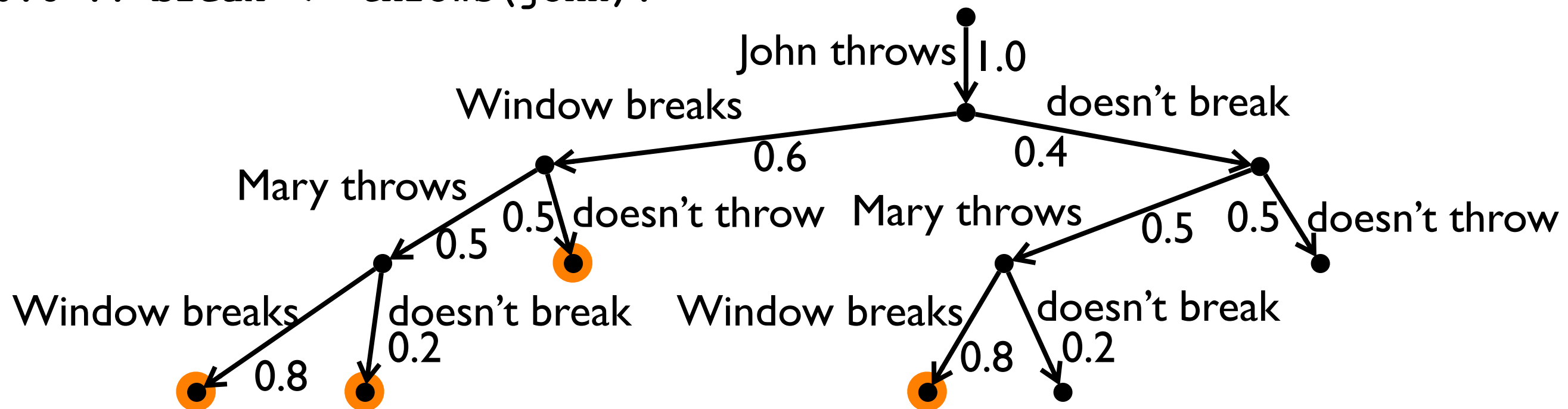
sbhg e(10)	sb g e(10)	sbh e(10)	sb
shg e(10)	s g	s h	s
bhg	b g	bh	b
hg	g	h	

Alternative view: CP-Logic

```
throws(john) .
0.5 :: throws(mary) .
```

probabilistic causal laws

```
0.8 :: break <- throws(mary) .
0.6 :: break <- throws(john) .
```



$$P(\text{break}) = 0.6 \times 0.5 \times 0.8 + 0.6 \times 0.5 \times 0.2 + 0.6 \times 0.5 + 0.4 \times 0.5 \times 0.8$$

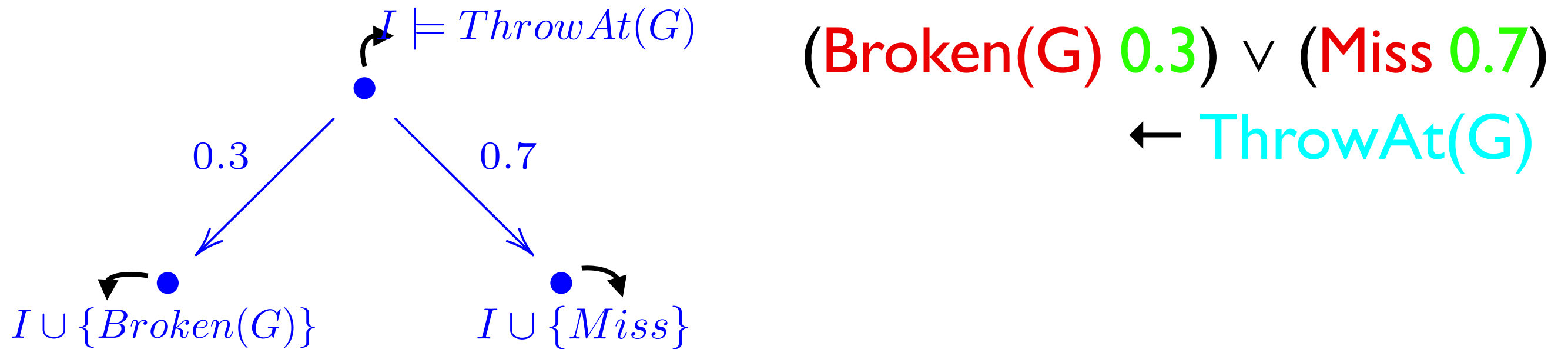
CP-logic [Vennekens et al.]

E.g., “**throwing** a rock at a glass **breaks** it with probability **0.3** and **misses** it with probability **0.7**”

$(\text{Broken}(G):0.3) \vee (\text{Miss } 0.7) \leftarrow \text{ThrowAt}(G).$

Note that the actual non-deterministic event (“rock flying at glass”) is implicit

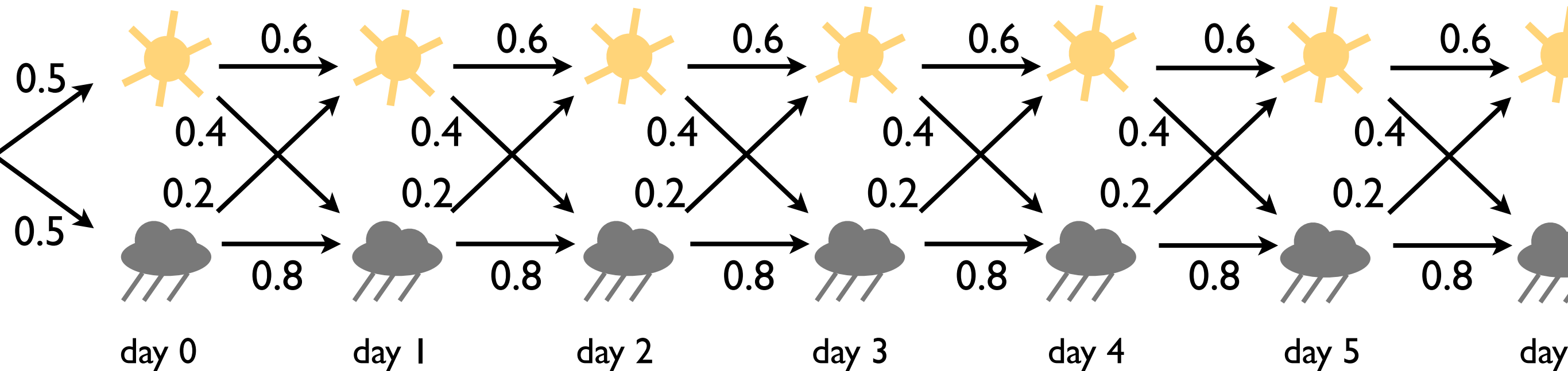
Semantics



- Probability tree is an execution model of theory iff:
- Each tree-transition **matches** causal law
 - The tree cannot be extended
 - Each execution model defines the same probability distribution over final states

ProbLog by example:

Rain or sun?



```
0.5::weather(sun,0) ; 0.5::weather(rain,0) .
```

```
0.6::weather(sun,T) ; 0.4::weather(rain,T)  
    :- T>0, Tprev is T-1, weather(sun,Tprev) .
```

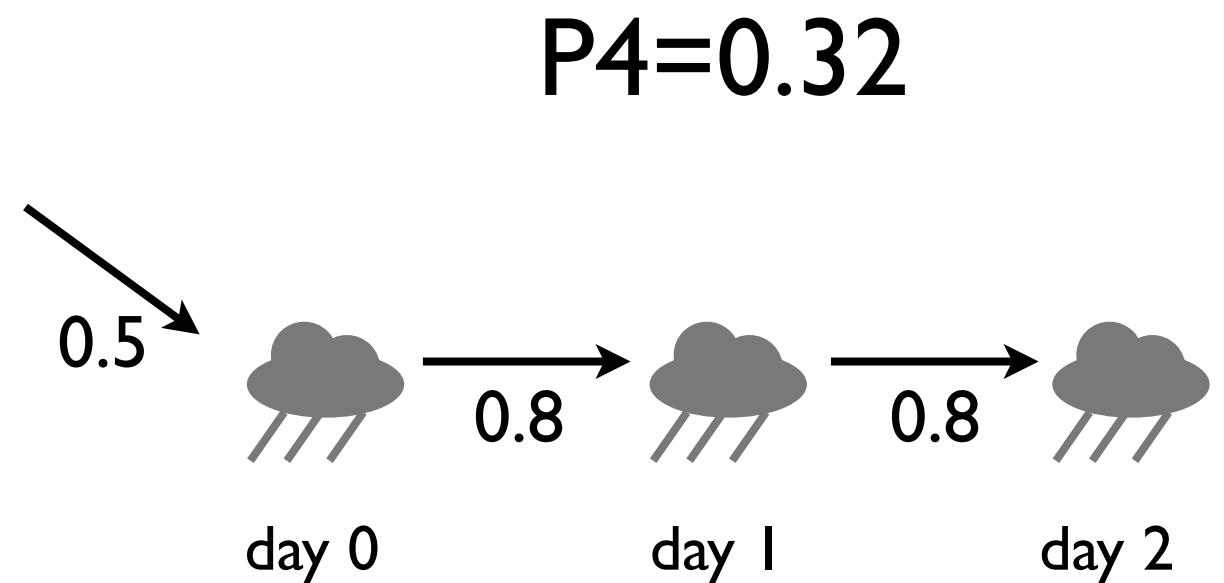
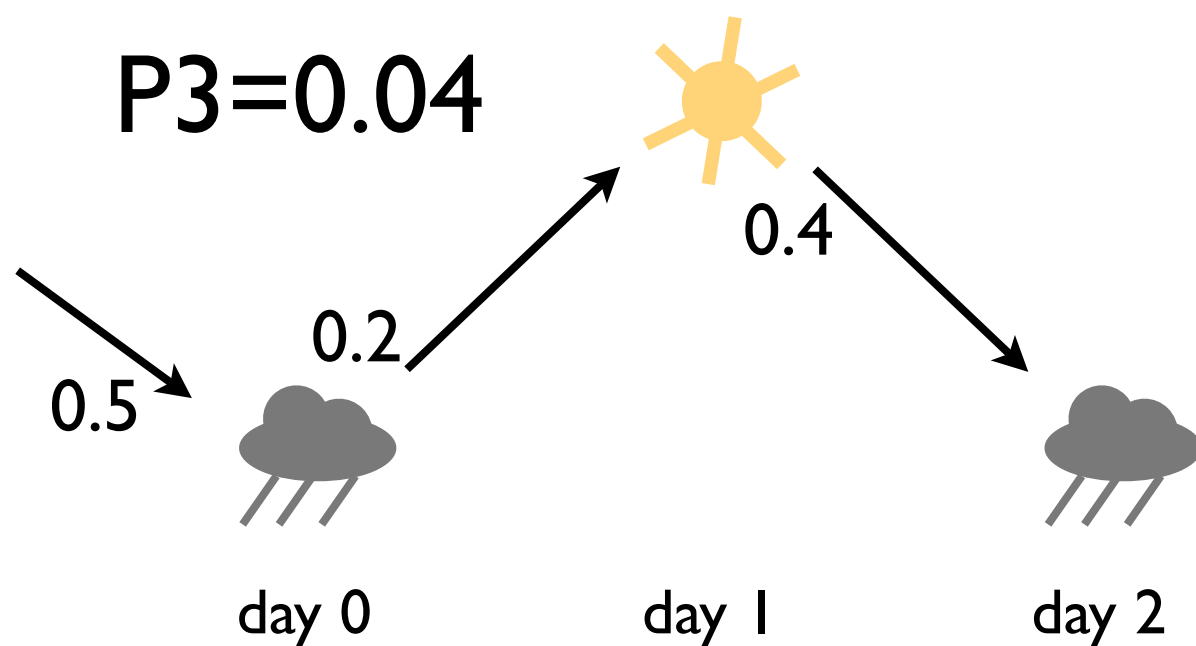
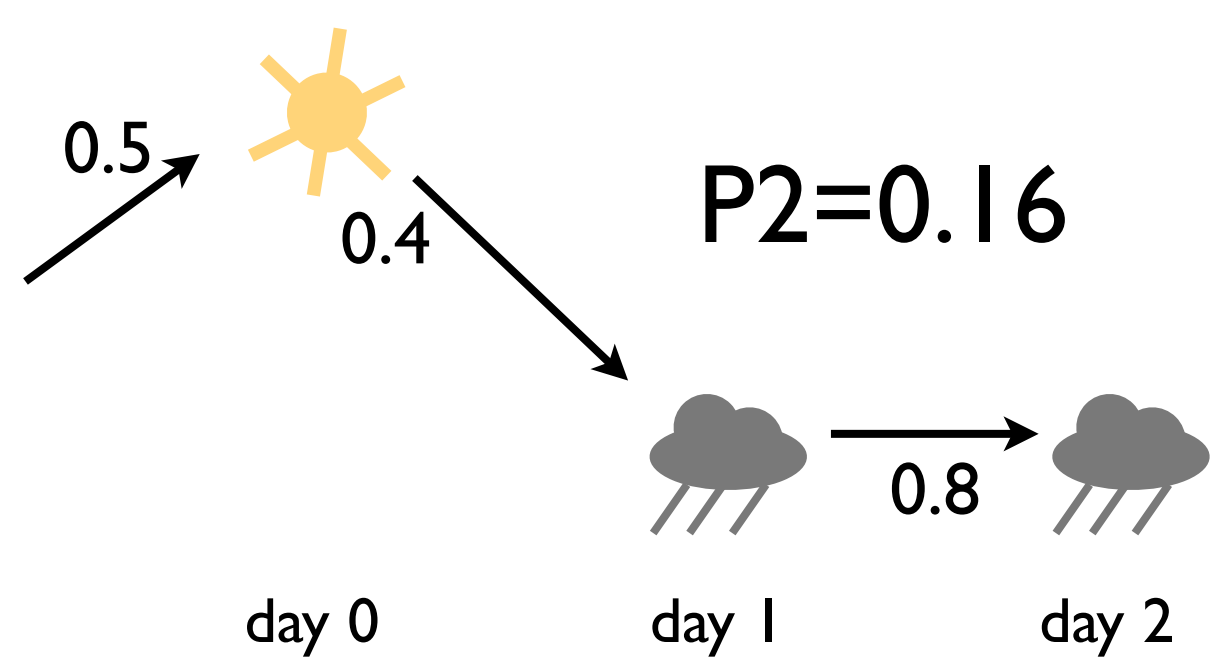
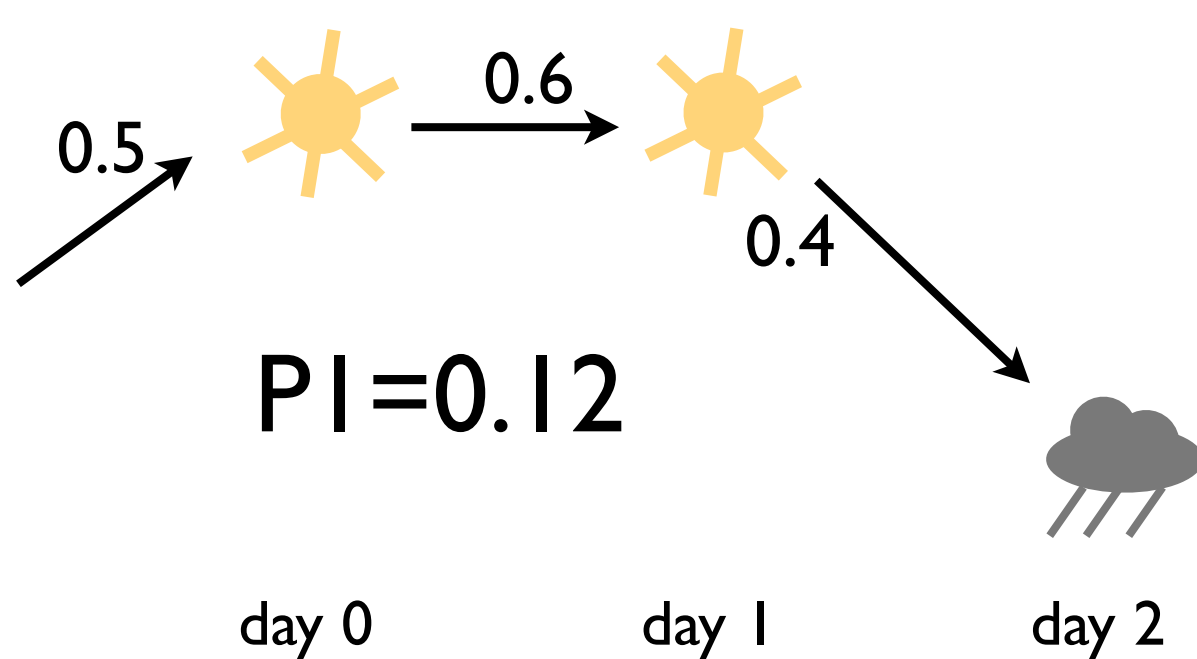
```
0.2::weather(sun,T) ; 0.8::weather(rain,T)  
    :- T>0, Tprev is T-1, weather(rain,Tprev) .
```

infinite possible worlds! BUT: finitely many partial worlds suffice to answer any given ground query

Possible worlds

?- weather(rain,2) .

$$P = P1 + P2 + P3 + P4$$



Distributional Clauses (DC)

- Discrete- and continuous-valued random variables

random variable

Defines a generative process (as for CP-logic)
Tree can become infinitely wide
Sampling
Well-defined under reasonable

distribution

```
length(Obj) ~ gaussian(6  
stackable(Obj1, Obj2) :-
```

```
length(Obj, glass) .
```

```
≈length(Obj1) ≥ ≈length(Obj2),  
≈width(Obj1) ≥ ≈width(Obj2) .
```

**comparing values of
random variables**

```
ontype(Obj, plate) ~ finite([0 : glass, 0.0024 : cup,  
                             0 : pitcher, 0.8676 : plate,  
                             0.0284 : bowl, 0 : serving,  
                             0.1016 : none])
```

```
:- obj(Obj), on(Obj, O2), type(O2, plate) .
```

**random variable with
discrete distribution**



Distributional Clauses (DC)

- Defines a generative process (as for CP-logic)
- Tree can become infinitely wide
 - Sampling ...
- Well-defined under reasonable assumptions

ProbLog

- **probabilistic choices** + their **consequences**
- probability distribution over **possible worlds**
- how to efficiently answer **questions?**
 - most probable world (MPE inference)
 - probability of query (computing marginals)
 - probability of query given evidence

Summary: ProbLog Syntax

- input database: ground facts

```
person(bob) .
```

- probabilistic facts

```
0.5::stress(bob) .
```

- annotated disjunctions

```
0.5::stress(X) :- person(X) .  
0.4::a(X) ; 0.3::b(X) ; 0.2::c(X) ; 0.1::d(X) :- q(X) .  
0.5::weather(sun,0) ; 0.5::weather(rain,0) .
```

- flexible probabilities

```
P::pack(Item) :- weight(Item,W), P is 1.0/W.
```

- Prolog clauses

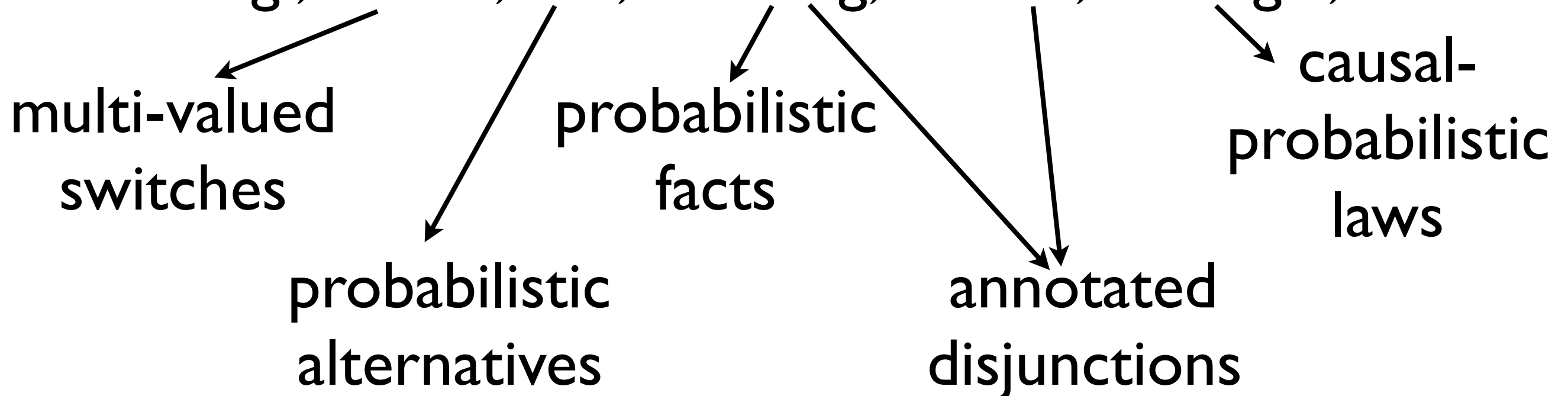
```
smokes(X) :- influences(Y,X), smokes(Y) .  
excess([I|R],Limit) :- \+pack(I), excess(R,Limit) .
```

Probabilistic Logic Programming

Distribution Semantics [Sato, ICLP 95]:
probabilistic choices + logic program
→ distribution over possible worlds

OVERVIEW paper [Kimmig, De Raedt, Arxiv, MLJ 15]

e.g., PRISM, ICL, ProbLog, LPADs, CP-logic, ...



Probabilistic databases

programming versus database query language
different types of queries

ProducesProduct

Company	Product	P
sony	walkman	0.96
microsoft	mac_os_x	0.96
ibm	personal_computer	0.96
microsoft	mac_os	0.9
adobe	adobe_indesign	0.9
adobe	adobe_dreamweaver	0.87
...

HeadquarteredIn

Company	City	P
microsoft	redmond	1.00
ibm	san_jose	0.99
emirates_airlines	dubai	0.93
honda	torrance	0.93
horizon	seattle	0.93
egyptair	cairo	0.93
adobe	san_jose	0.93
...

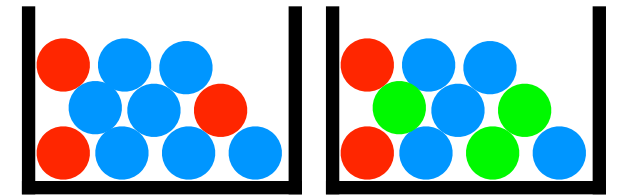
```
select x.Product, x.Company
from ProducesProduct x, HeadquarteredIn y
where x.Company=y.Company and
y.City='san_jose'
```


Probabilistic Programs

- Distributional clauses / PLP similar in spirit
 - to e.g. BLOG, ... but embedded in existing logic and programming language
 - to e.g. Church but use of logic instead of functional programming ...
 - natural possible world semantics and link with prob. databases.
 - somewhat harder to do meta-programming

Church by example:

A bit of gambling



- toss (biased) coin & draw ball from each urn
- win if (heads and a red ball) or (two balls of same color)

```
(define heads (mem (lambda () (flip 0.4))))  
(define color1 (mem (lambda () (if (flip 0.3) 'red 'blue))))  
(define color2 (mem (lambda ()  
                      (multinomial '(red green blue) '(0.2 0.3 0.5))))))  
(define redball (or (equal? (color1) 'red) (equal? (color2) 'red)))  
(define win1 (and (heads) redball))  
(define win2 (equal? (color1) (color2)))  
(define win (or win1 win2))
```

Markov Logic

Key differences

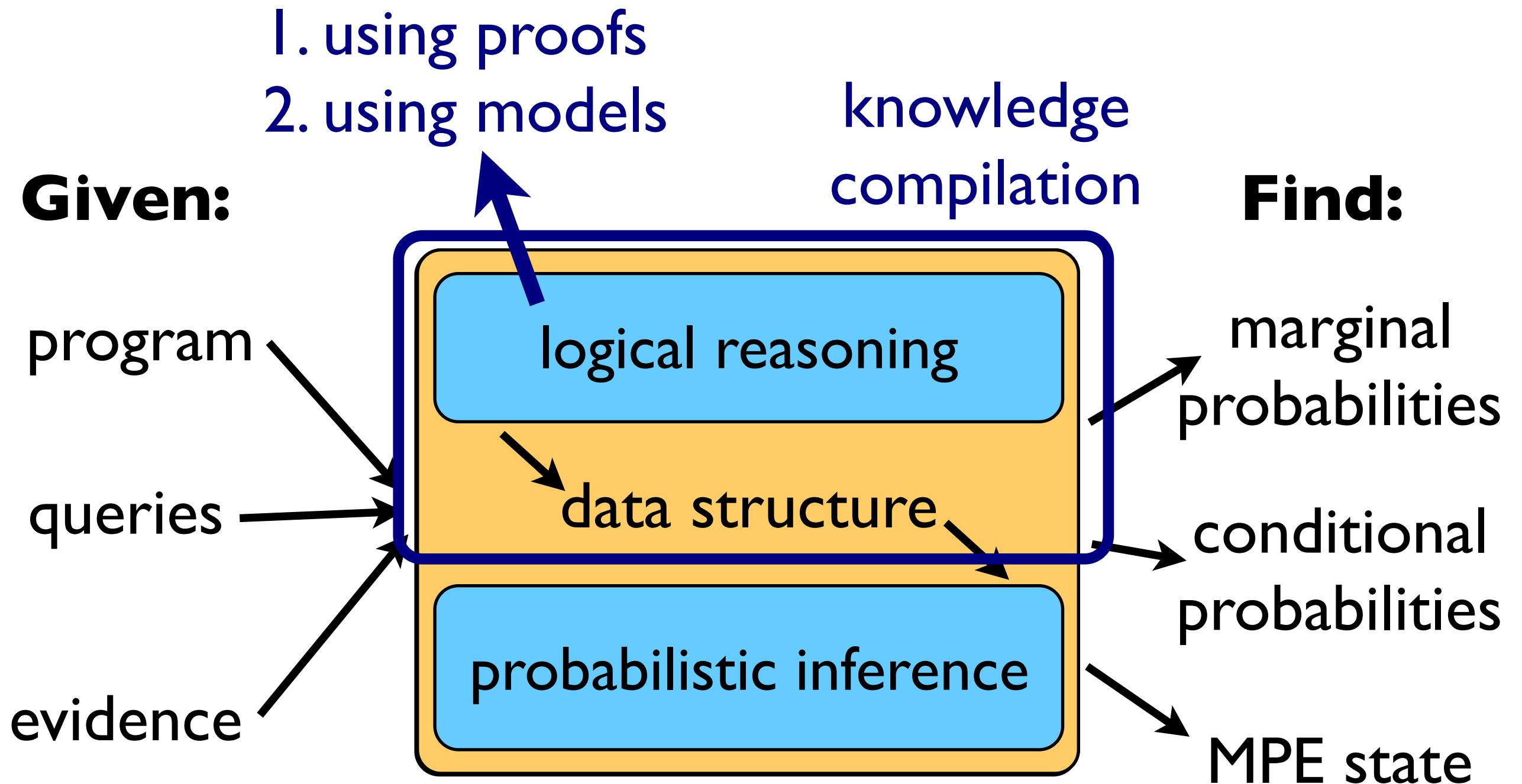
- programming language
- Pro(b)log uses least-fix point semantics
- can express transitive closure of relation
- this cannot be expressed in FOL (and Markov Logic), requires second order logic
- $p(X,Y) \text{ :- } p(X,Z), p(Z,Y).$

PART II: Inference

Inference in PLP

- As in Prolog and logic programming
 - **proof**-based
- As in Answer Set Programming
 - **model** based
- As in Probabilistic Programming
 - **sampling**

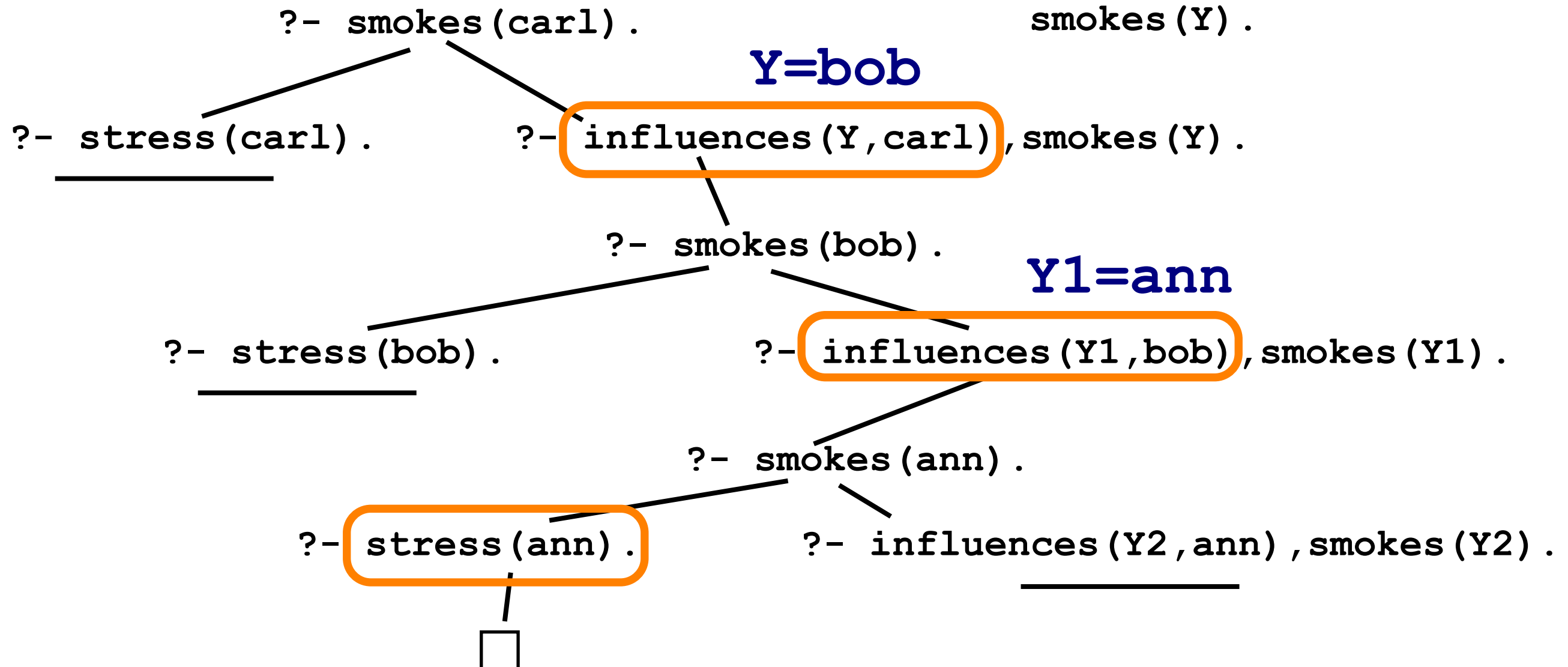
Inference



Proofs in ProbLog

```
0.8::stress(ann).
0.6::influences(ann,bob).
0.2::influences(bob,carl).
```

```
smokes(X) :- stress(X).
smokes(X) :-
    influences(Y,X),
    smokes(Y).
```



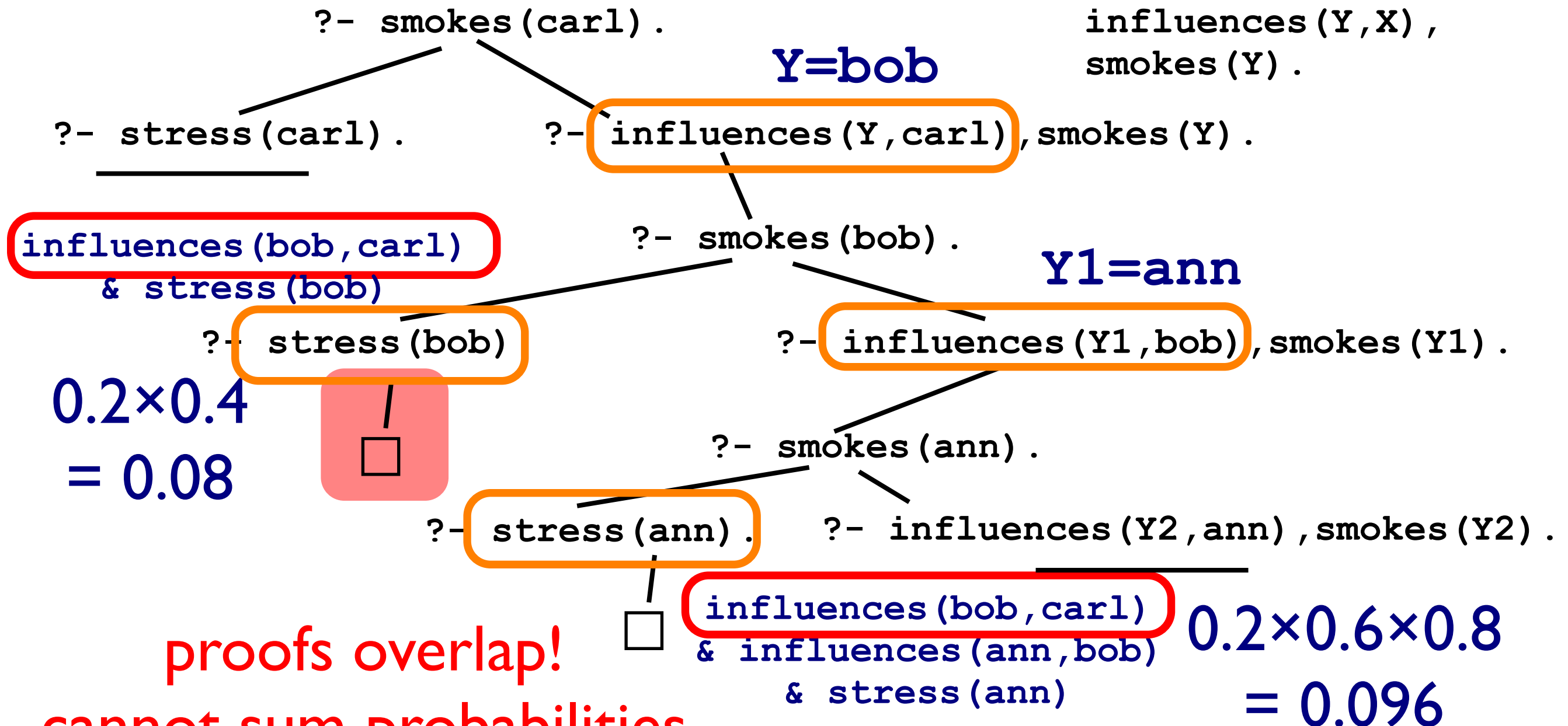
$\text{influences}(\text{bob}, \text{carl}) \ \& \ \text{influences}(\text{ann}, \text{bob}) \ \& \ \text{stress}(\text{ann})$

probability of proof = $0.2 \times 0.6 \times 0.8 = 0.096$

Proofs in ProbLog

```
0.8::stress(ann).
0.4::stress(bob).
0.6::influences(ann,bob).
0.2::influences(bob,carl).
```

```
smokes(X) :- stress(X).
smokes(X) :-
    influences(Y,X),
    smokes(Y).
```



proofs overlap!
cannot sum probabilities
(disjoint-sum-problem)

Disjoint-Sum-Problem

possible worlds

solution: knowledge compilation

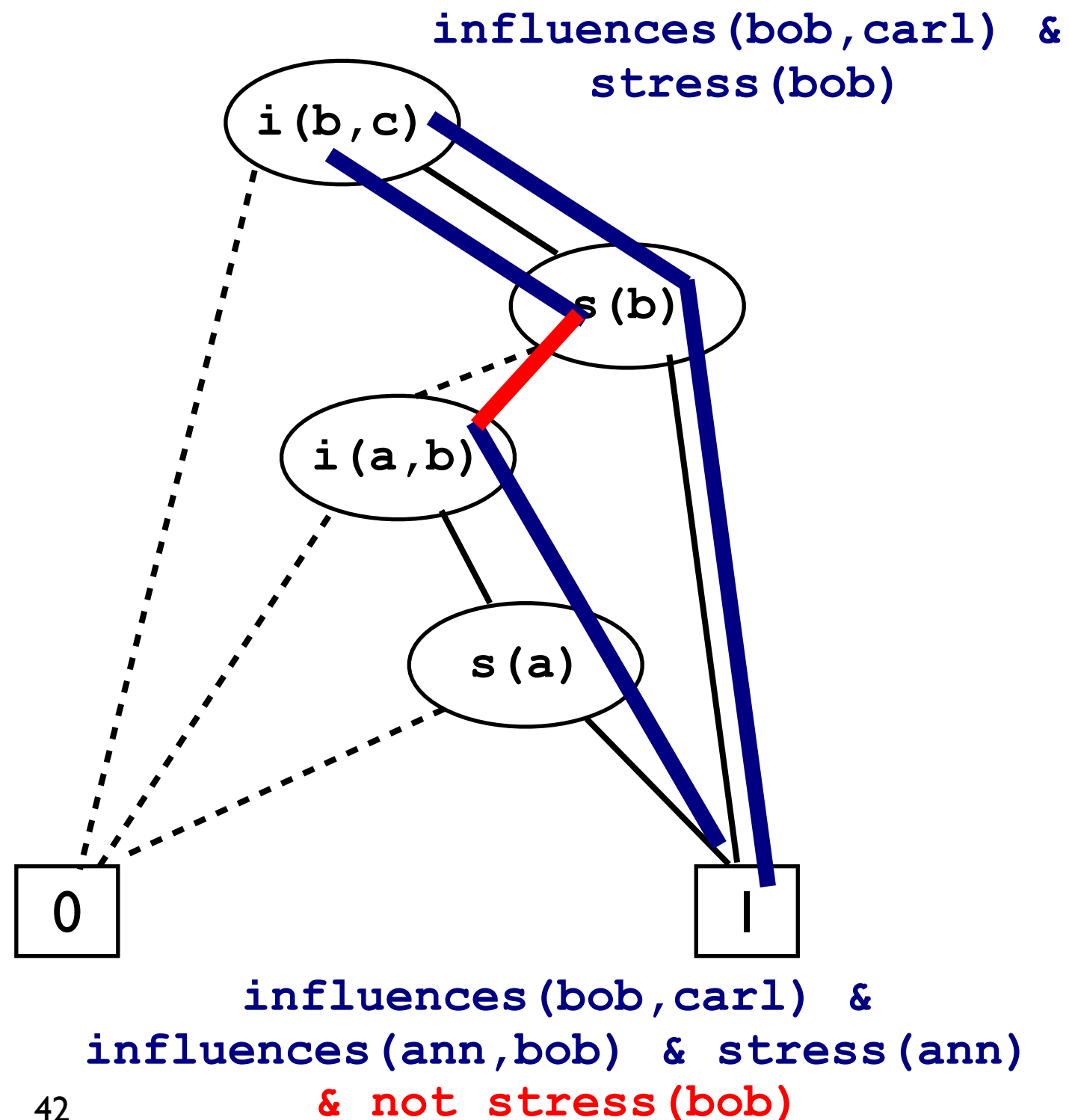
<code>infl(bob,carl) & infl(ann,bob) & st(ann) & \+st(bob)</code>	0.0576
<code>infl(bob,carl) & infl(ann,bob) & st(ann) & st(bob)</code>	0.0384
<code>infl(bob,carl) & \+infl(ann,bob) & st(ann) & st(bob)</code>	0.0256
<code>infl(bob,carl) & infl(ann,bob) & \+st(ann) & st(bob)</code>	0.0096
<code>infl(bob,carl) & \+infl(ann,bob) & \+st(ann) & st(bob)</code>	0.0064

... `influences(bob,carl) & stress(bob)` $\Sigma = 0.1376$

sum of proof probabilities: $0.096 + 0.08 = 0.1760$

Binary Decision Diagrams [Bryant 86]

- compact graphical representation of Boolean formula
- automatically disjoins proofs
- popular in many branches of CS



Current Approach

(ProbLog2)

```
0.4::heads(1).  
0.7::heads(2).  
0.5::heads(3).  
win :- heads(1).  
win :- heads(2),  
      heads(3).
```

Find relevant ground
program for queries &
evidence

win

Weighted CNF

use weighted model
counting / satisfiability

```
win :- heads(1).  
win :- heads(2), heads(3).
```

$\text{win} \leftrightarrow h(1) \vee (h(2) \wedge h(3))$
may require loop-
breaking

$(\neg \text{win} \vee h(1) \vee h(2))$
 $\wedge (\neg \text{win} \vee h(1) \vee h(3))$
 $\wedge (\text{win} \vee \neg h(1))$
 $\wedge (\text{win} \vee \neg h(2) \vee \neg h(3))$

use
standard
tool

$h(1) \rightarrow 0.4$	$h(2) \rightarrow 0.7$	$h(3) \rightarrow 0.5$
$\neg h(1) \rightarrow 0.6$	$\neg h(2) \rightarrow 0.3$	$\neg h(3) \rightarrow 0.5$

ProbLog \rightarrow CNF

```
?- smokes(carl) .
```

```
0.8::stress(ann) .  
0.4::stress(bob) .  
0.6::influences(ann,bob) .  
0.2::influences(bob,carl) .
```

```
smokes(X) :- stress(X) .  
smokes(X) :-  
    influences(Y,X) ,  
    smokes(Y) .
```

- Find relevant ground rules by backward reasoning

```
smokes(carl) :- influences(bob,carl) , smokes(bob) .  
smokes(bob) :- stress(bob) .  
smokes(bob) :- influences(ann,bob) , smokes(ann) .  
smokes(ann) :- stress(ann) .
```

- Convert to propositional logic formula

may require
loop-breaking

$$\begin{aligned} & \text{sm}(c) \leftrightarrow (\text{i}(b,c) \wedge \text{sm}(b)) \\ & \wedge \text{sm}(b) \leftrightarrow (\text{st}(b) \vee (\text{i}(a,b) \wedge \text{sm}(a))) \\ & \wedge \text{sm}(a) \leftrightarrow \text{st}(a) \end{aligned}$$

- Rewrite in CNF (as usual)

Weighted

$$P(Q) = \sum_{F \cup R \models Q} \prod_{f \in F} p(f) \prod_{f \notin F} 1 - p(f)$$

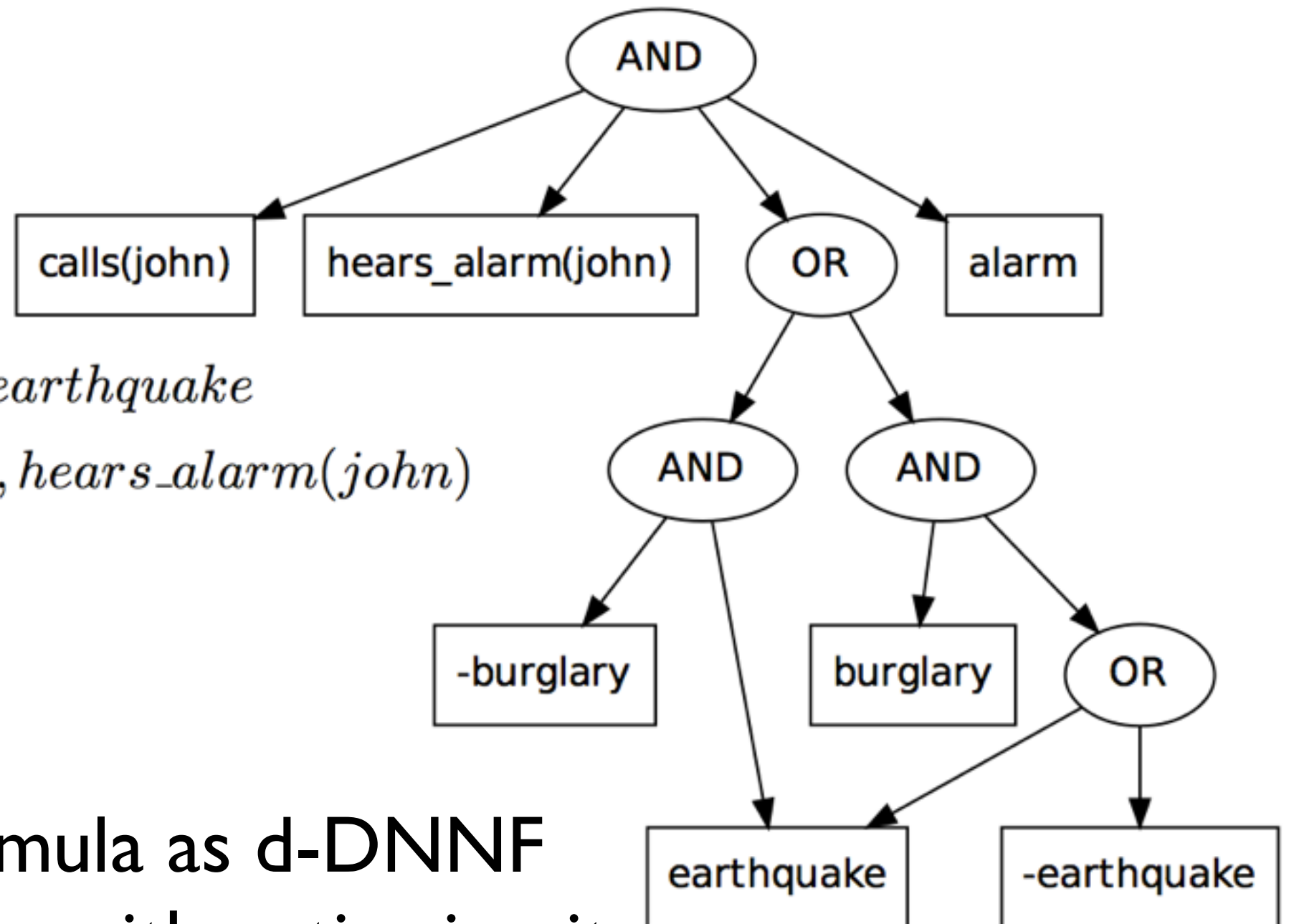
propositional formula in conjunctive normal form (CNF)
given by ProbLog program & query

$$WMC(\phi) = \sum_{I_V \models \phi} \prod_{l \in I_V} w(l)$$

interpretations (truth
value assignments) of
propositional variables
possible worlds

weight
of literal
for $p::f$,
 $w(f) = p$
 $w(\text{not } f) = 1 - p$

WMC using d-DNNFs



$alarm \leftrightarrow burglary \vee earthquake$

$calls(john) \leftrightarrow alarm, hears_alarm(john)$

$calls(john)$

1. represent formula as d-DNNF
2. transform into arithmetic circuit
3. evaluate bottom-up

Current Approach

(ProbLog2)

```
0.4::heads(1).
0.7::heads(2).
0.5::heads(3).
win :- heads(1).
win :- heads(2),
      heads(3).
```

Find relevant ground
program for queries &
evidence

win

Weighted CNF

use weighted model
counting / satisfiability

```
win :- heads(1).
win :- heads(2), heads(3).
```

$\text{win} \leftrightarrow h(1) \vee (h(2) \wedge h(3))$
may require loop-
breaking

$(\neg \text{win} \vee h(1) \vee h(2))$
 $\wedge (\neg \text{win} \vee h(1) \vee h(3))$
 $\wedge (\text{win} \vee \neg h(1))$
 $\wedge (\text{win} \vee \neg h(2) \vee \neg h(3))$

use
standard
tool

$h(1) \rightarrow 0.4$	$h(2) \rightarrow 0.7$	$h(3) \rightarrow 0.5$
$\neg h(1) \rightarrow 0.6$	$\neg h(2) \rightarrow 0.3$	$\neg h(3) \rightarrow 0.5$

Inference for DC

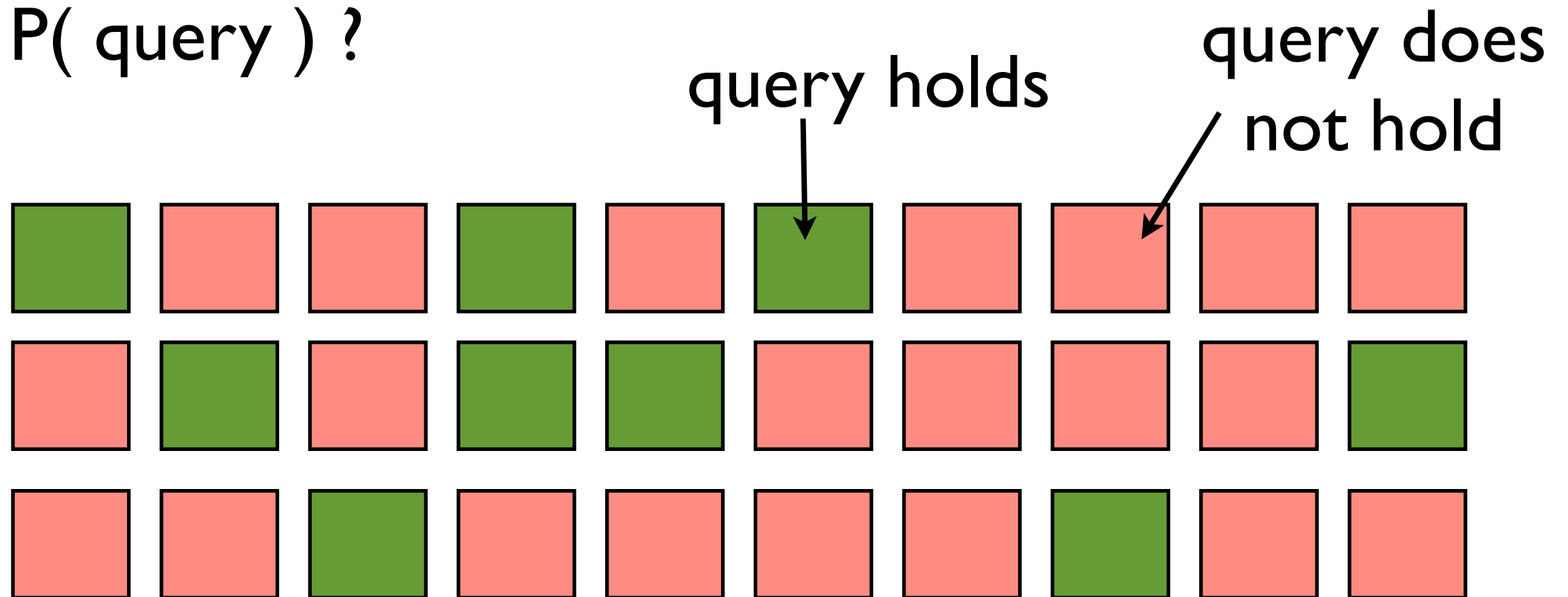
SLD- Resolution

Likelihood Weighting

$n \sim \text{uniform}([1, 2, 3, 4, 5, 6, 7, 8, 9, 10])$.
 $\text{color}(X) \sim \text{uniform}([\text{grey}, \text{blue}, \text{black}]) \leftarrow \text{material}(X) \sim = \text{metal}$.
 $\text{color}(X) \sim \text{uniform}([\text{black}, \text{brown}]) \leftarrow \text{material}(X) \sim = \text{wood}$.
 $\text{material}(X) \sim \text{finite}([0.3:\text{wood}, 0.7:\text{metal}]) \leftarrow n \sim = N, \text{between}(1, N, X)$.
 $\text{drawn}(Y) \sim \text{uniform}(L) \leftarrow n \sim = N, \text{findall}(X, \text{between}(1, N, X), L)$.
 $\text{size}(X) \sim \text{beta}(2, 3) \leftarrow \text{material}(X) \sim = \text{metal}$.
 $\text{size}(X) \sim \text{beta}(4, 2) \leftarrow \text{material}(X) \sim = \text{wood}$.

Sampling

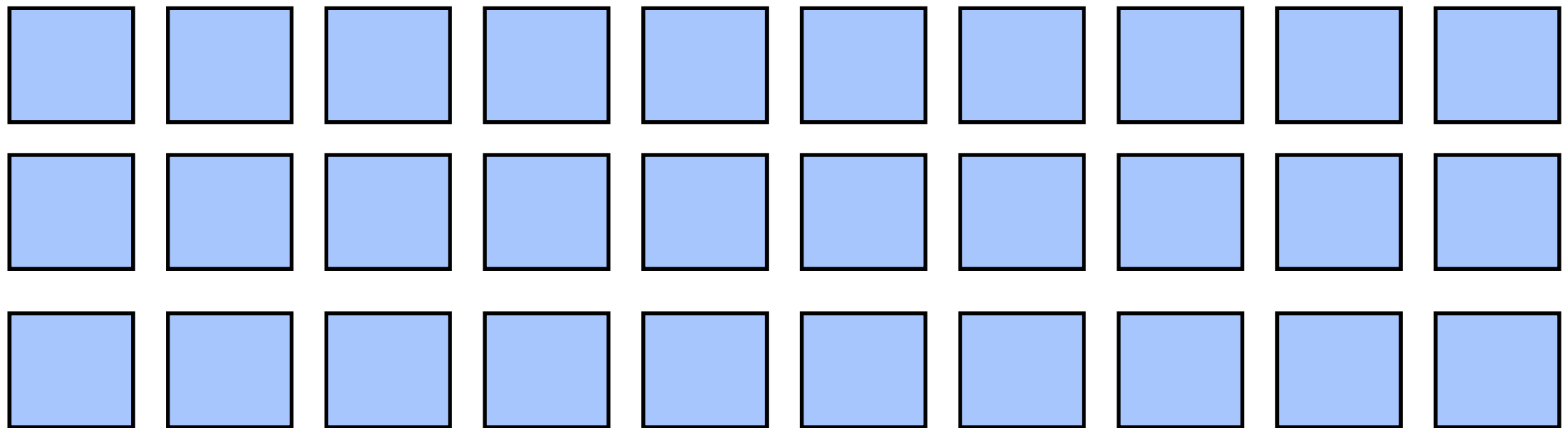
- $P(\text{query})$?



$$P(\text{query}) \approx \frac{\# \text{ query holds}}{\# \text{ worlds sampled}}$$

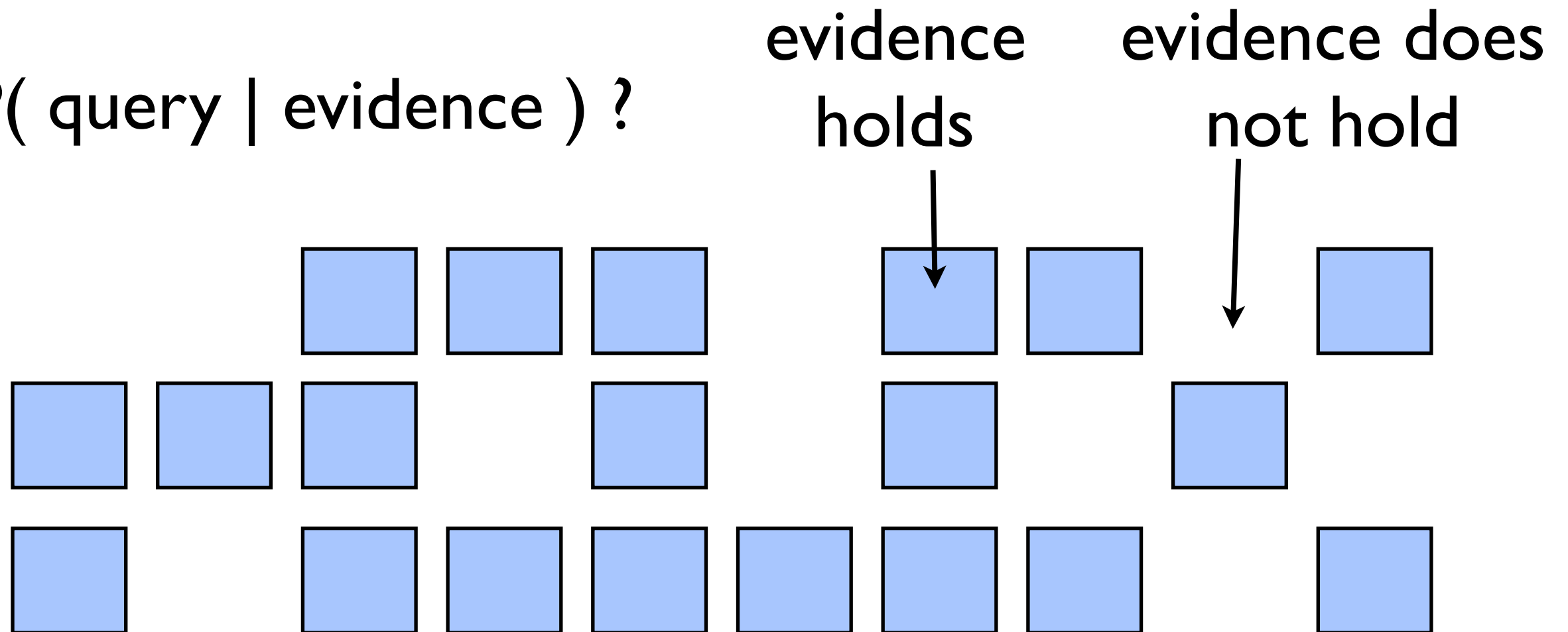
Rejection Sampling

- $P(\text{query} \mid \text{evidence})$?

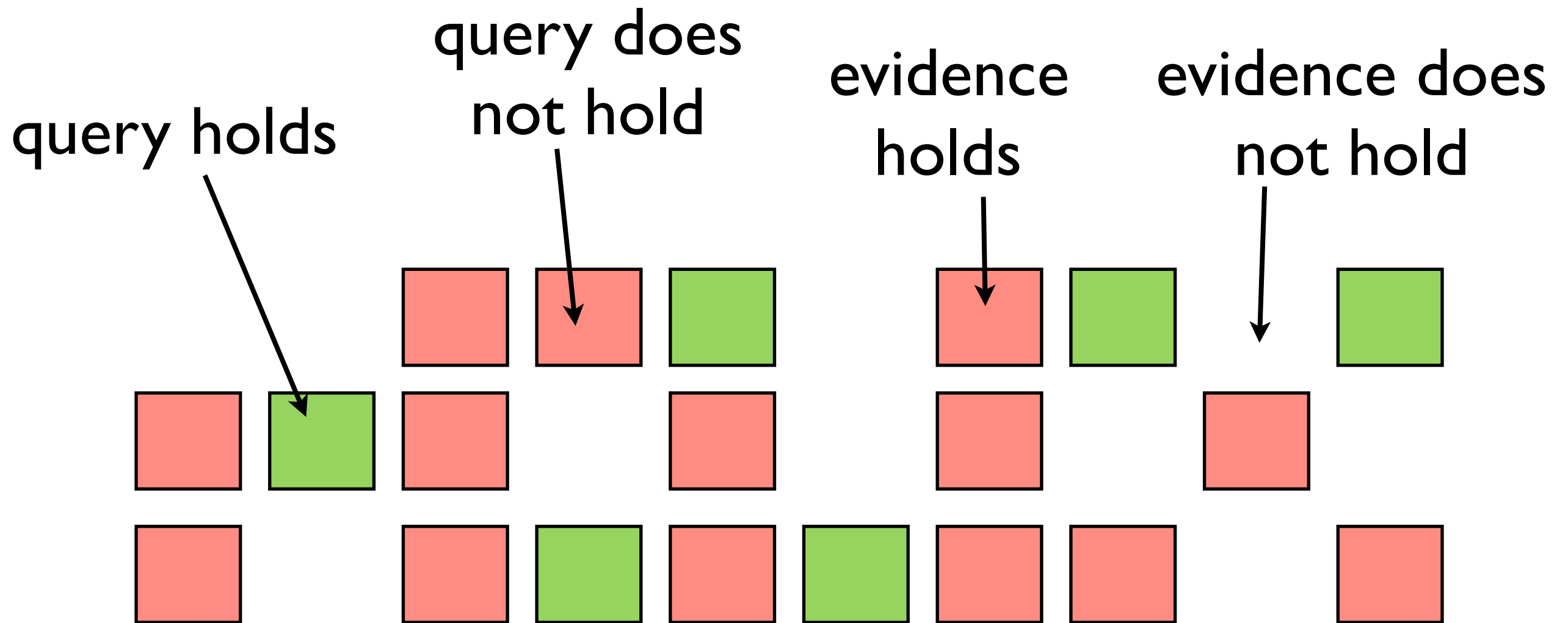


Rejection Sampling

- $P(\text{query} \mid \text{evidence})$?



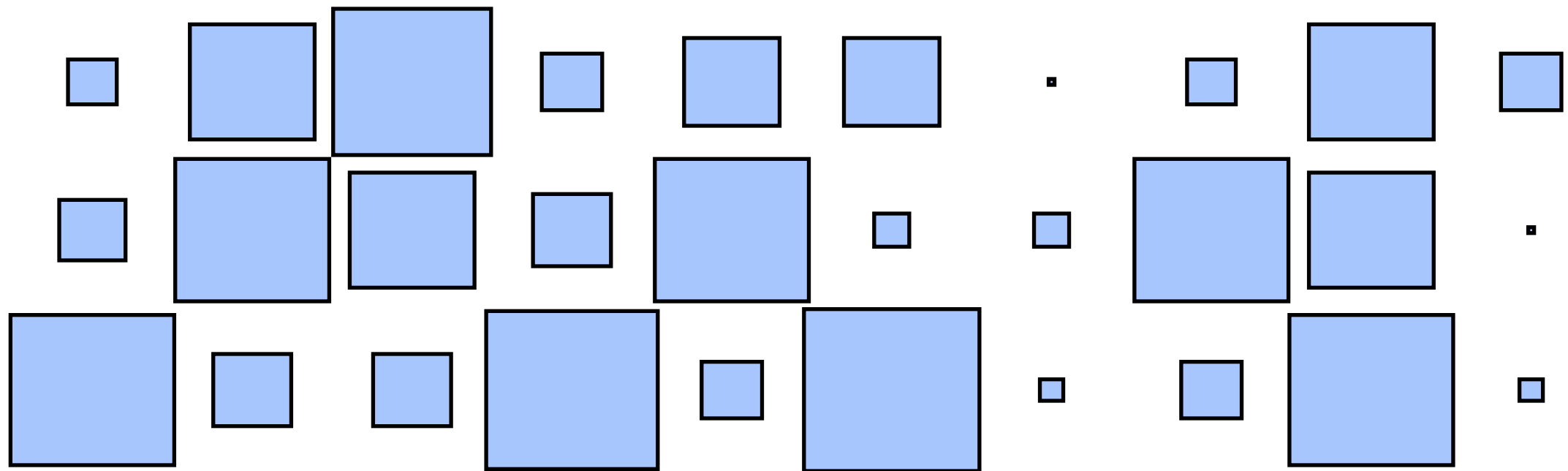
Rejection Sampling



$$P(\text{query} \mid \text{evidence}) \approx \frac{\# \text{ query \& evidence holds}}{\# \text{ evidence holds}}$$

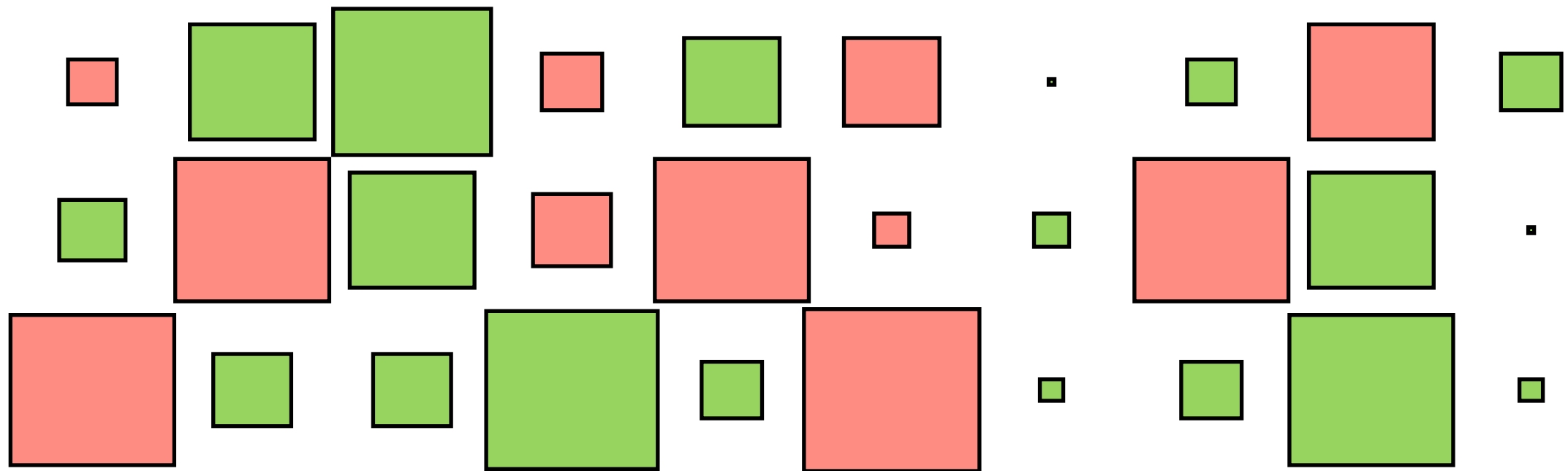
Likelihood Weighting

- $P(\text{query} \mid \text{evidence})$?



Likelihood Weighting

- $P(\text{query} \mid \text{evidence})$?



LW for DC

Given a goal G and the global variables $w_q^{(i)}, iq, x^{P(i)}$, applying a rule produces a new goal G' and modifies the global variables:

1. G' is the new goal obtained from G using a kind of SLD-resolution step;
2. if a new variable r is sampled with value v ,
 - set $w_q^{(i)} \leftarrow w_q^{(i)} \frac{p(r=v|x^{P(i)})}{g(r=v|x^{P(i)})}$ (based on LW) and
 - $x^{P(i)} \leftarrow x^{P(i)} \cup \{r = v\}$.

In addition, if $r = Val \in iq$ with r grounded, then:

- $iq \leftarrow iq\theta$ with $\theta = \{Val = v\}$.
3. if a new atom a is proved set $x^{P(i)} \leftarrow x^{P(i)} \cup \{a\}$.

$$n \sim \text{uniform}([1, 2, 3, 4, 5, 6, 7, 8, 9, 10]). \quad (6)$$

$$\text{color}(X) \sim \text{uniform}([\text{grey}, \text{blue}, \text{black}]) \leftarrow \text{material}(X) \sim = \text{metal}. \quad (7)$$

$$\text{color}(X) \sim \text{uniform}([\text{black}, \text{brown}]) \leftarrow \text{material}(X) \sim = \text{wood}. \quad (8)$$

$$\text{material}(X) \sim \text{finite}([0.3:\text{wood}, 0.7:\text{metal}]) \leftarrow n \sim = N, \text{between}(1, N, X). \quad (9)$$

$$\text{drawn}(Y) \sim \text{uniform}(L) \leftarrow n \sim = N, \text{findall}(X, \text{between}(1, N, X), L). \quad (10)$$

$$\text{size}(X) \sim \text{beta}(2, 3) \leftarrow \text{material}(X) \sim = \text{metal}. \quad (11)$$

$$\text{size}(X) \sim \text{beta}(4, 2) \leftarrow \text{material}(X) \sim = \text{wood}. \quad (12)$$

$$\vdash 1: (\text{color}(2) \sim = \text{black}); w_q^{(i)} = 1; x^{P(i)} = \emptyset$$

↓ 2b on (8) :

$$9: (\text{material}(2) \sim = \text{wood}, \text{sample}(\text{color}(2), \mathcal{D}_{\text{color}(2)}), \text{color}(2) \sim = \text{black})$$

$$\downarrow w_q^{(i)} = 1; x^{P(i)} = \{n = 3, \text{material}(2) = \text{wood}\}$$

↓ 2a :

$$10: (\text{sample}(\text{color}(2), \mathcal{D}_{\text{color}(2)}), \text{color}(2) \sim = \text{black}); w = 1; x^{P(i)} = \{n = 3, \text{material}(2) = \text{wood}\}$$

↓ 3a :

$$11: (\text{color}(2) \sim = \text{black}); w_q^{(i)} = 1/3; x^{P(i)} = \{n = 3, \text{material}(2) = \text{wood}, \text{color}(2) = \text{black}\}$$

↓ 1a :

$$12: \square; w_q^{(i)} = 1/3; x^{P(i)} = \{n = 3, \text{material}(2) = \text{wood}, \text{color}(2) = \text{black}\}$$

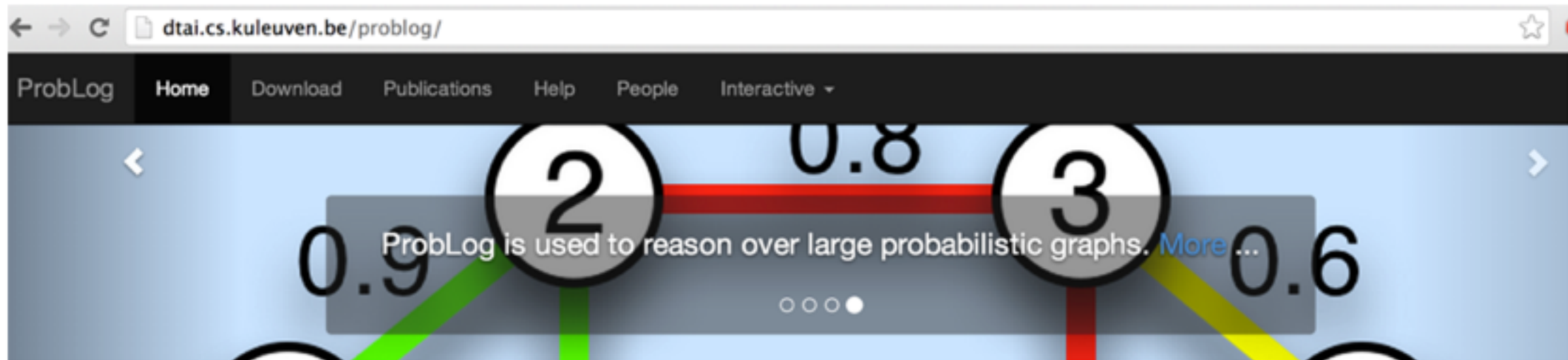
can cope with evidence like $\text{color}(1) = \text{color}(2)$

and $\text{size}(1) = 0.356$, $\text{size}(1) = \text{size}(2)$, ...

outperforms BLOG ... unification + LW

-1: (color(2) \sim black); $w_q^{(i)} = 1$; $x^{P(i)} = \emptyset$
 ↓ 2b on (7) :
 2: (material(2) \sim metal, sample(color(2), $\mathcal{D}_{\text{color}(2)}$), color(2) \sim black); $w_q^{(i)} = 1$; $x^{P(i)} = \emptyset$
 ↓ 2b on (9) :
 3: (n \sim N, between(1, N, 2), sample(material(2), $\mathcal{D}_{\text{material}(2)}$), material(2) \sim metal,
 sample(color(2), $\mathcal{D}_{\text{color}(2)}$), color(2) \sim black); $w_q^{(i)} = 1$; $x^{P(i)} = \emptyset$
 ↓ 2b on (6) :
 4: (sample(n, \mathcal{D}_n), n \sim N, between(1, \simeq (n), 2), sample(material(2), $\mathcal{D}_{\text{material}(2)}$),
 material(2) \sim metal, sample(color(2), $\mathcal{D}_{\text{color}(2)}$), color(2) \sim black); $w_q^{(i)} = 1$; $x^{P(i)} = \emptyset$
 ↓ 3b :
 5: (n \sim 3, between(1, 3, 2), sample(material(2), $\mathcal{D}_{\text{material}(2)}$), material(2) \sim metal,
 sample(color(2), $\mathcal{D}_{\text{color}(2)}$), color(2) \sim black); $w_q^{(i)} = 1$; $x^{P(i)} = \{n = 3\}$
 ↓ 2a followed by 1a
 6: (sample(material(2), $\mathcal{D}_{\text{material}(2)}$), material(2) \sim metal, sample(color(2),
 color(2) \sim black); $w_q^{(i)} = 1$; $x^{P(i)} = \{n = 3\}$
 ↓ 3b :
 7: (material(2) \sim metal, sample(color(2), $\mathcal{D}_{\text{color}(2)}$), color(2) \sim black)
 $w_q^{(i)} = 1$; $x^{P(i)} = \{n = 3, \text{material}(2) = \text{wood}\}$
 fail, backtracking to 1

http://dtai.cs.kuleuven.be/problog



Introduction.

Probabilistic logic programs are logic programs in which some of the facts are annotated with probabilities.

ProbLog is a tool that allows you to intuitively build programs that do not only encode **complex interactions** between a large sets of **heterogenous components** but also the inherent **uncertainties** that are present in real-life situations.

The engine tackles several tasks such as computing the marginals given evidence and learning from (partial) interpretations. ProbLog is a suite of efficient algorithms for various inference tasks. It is based on a conversion of the program and the queries and evidence to a weighted Boolean formula. This allows us to reduce the inference tasks to well-studied tasks such as weighted model counting, which can be solved using state-of-the-art methods known from the graphical model and knowledge compilation literature.

The Language. Probabilistic Logic Programming.

ProbLog makes it easy to express complex, probabilistic models.

```
0.3::stress(X) :- person(X).  
0.2::influences(X,Y) :- person(X), person(Y).
```

PART III: Learning

Parameter Learning

e.g., webpage classification model

for each *CLASS1*, *CLASS2* and each *WORD*

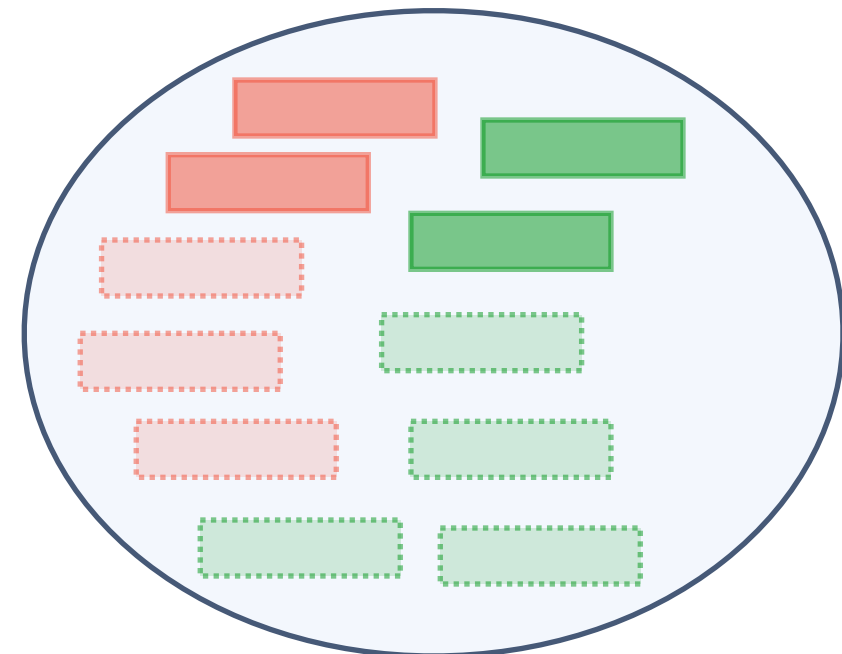
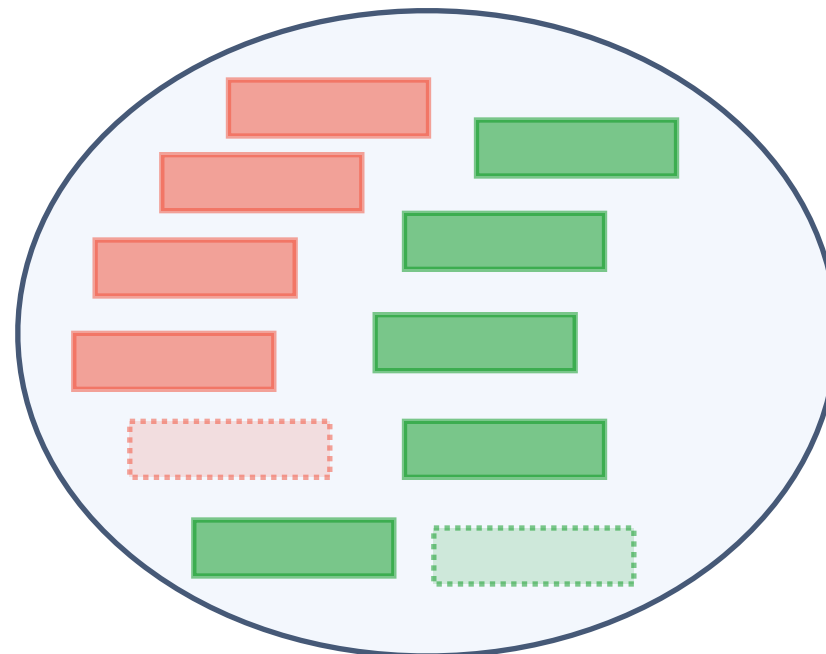
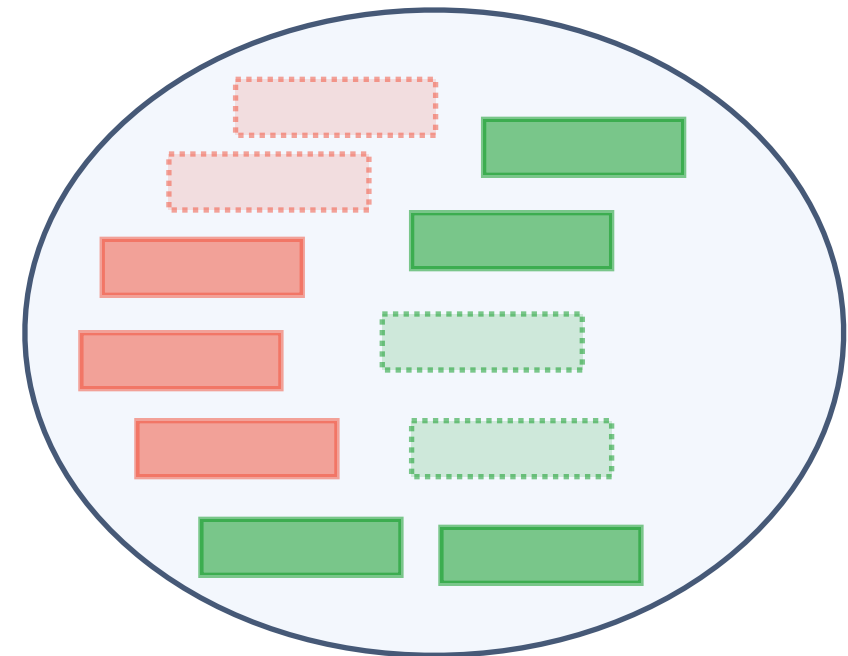
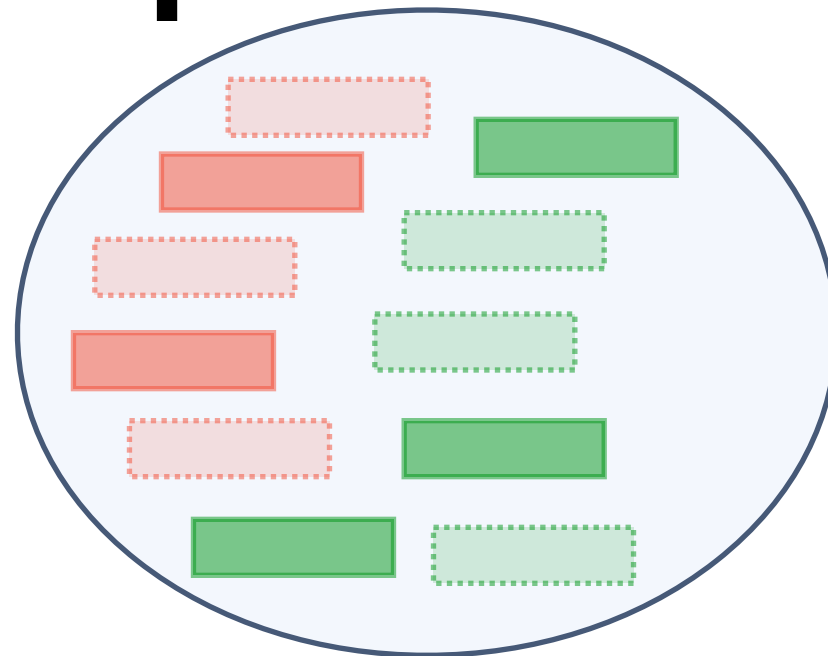
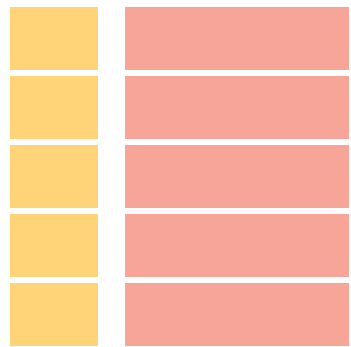
```
?? :: link_class(Source,Target,CLASS1,CLASS2).
```

```
?? :: word_class(WORD,CLASS).
```

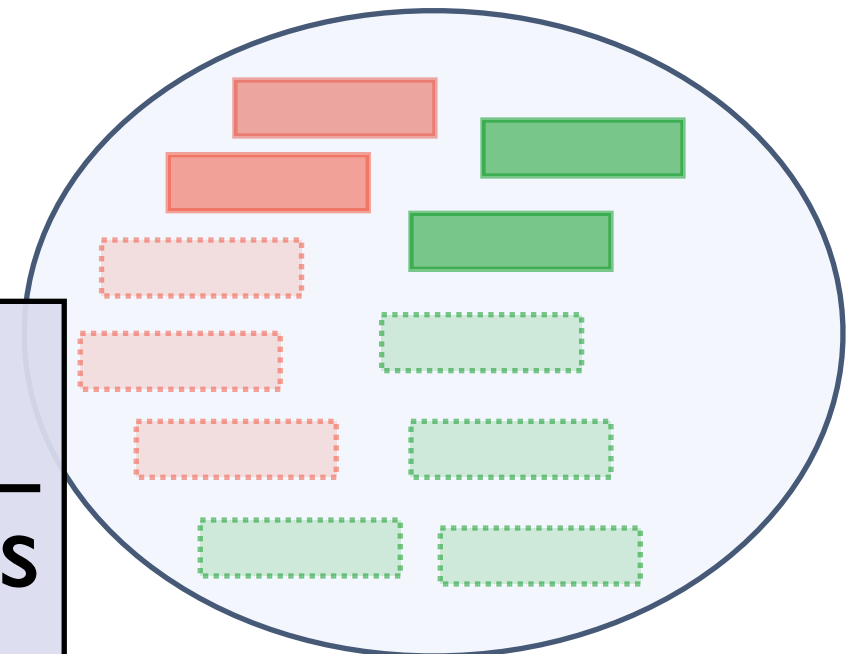
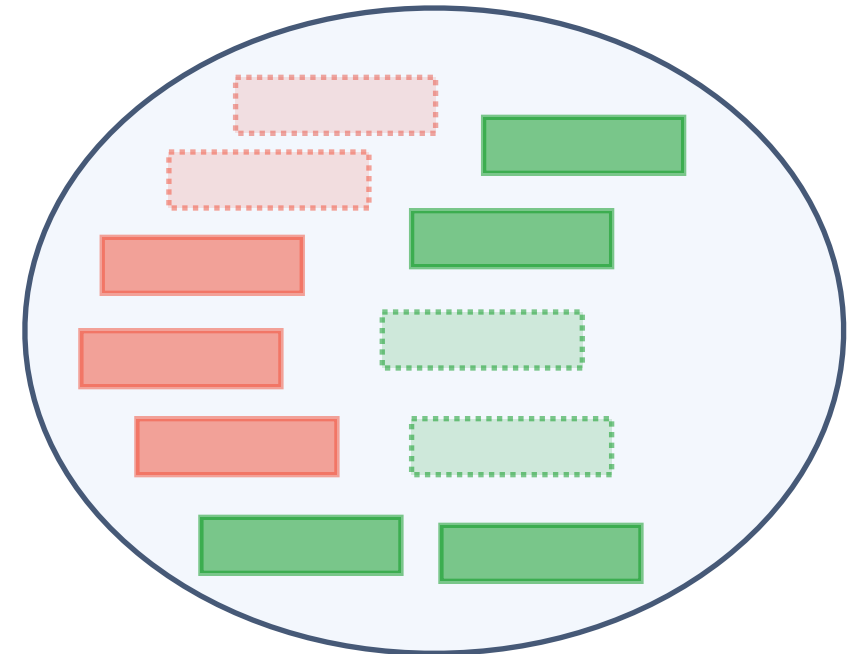
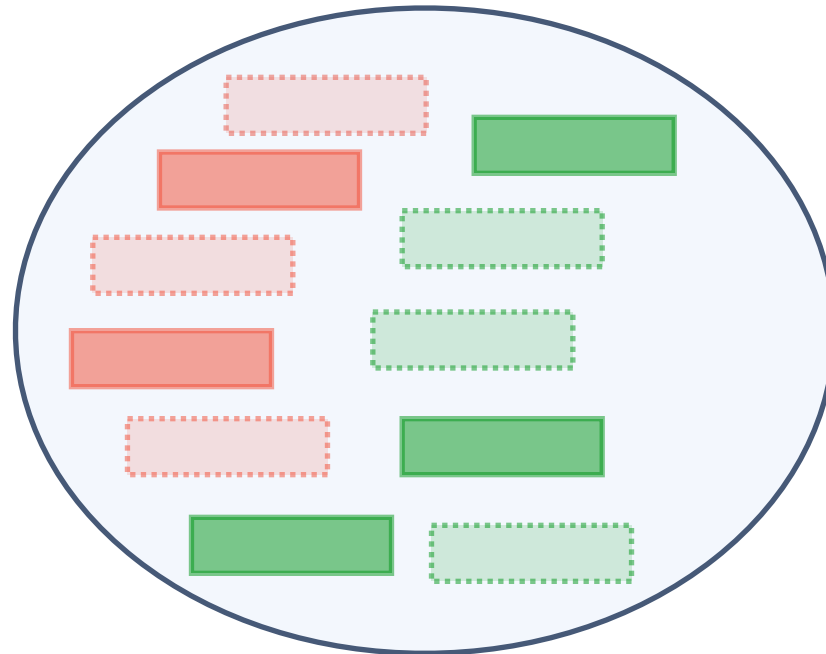
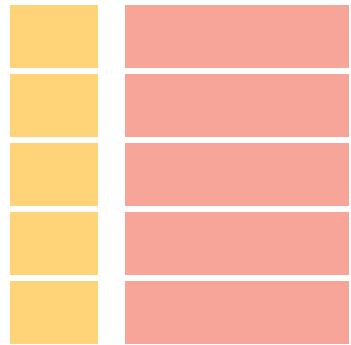
```
class(Page,C) :- has_word(Page,W), word_class(W,C).
```

```
class(Page,C) :- links_to(OtherPage,Page),  
class(OtherPage,OtherClass),  
link_class(OtherPage,Page,OtherClass,C).
```

Sampling Interpretations

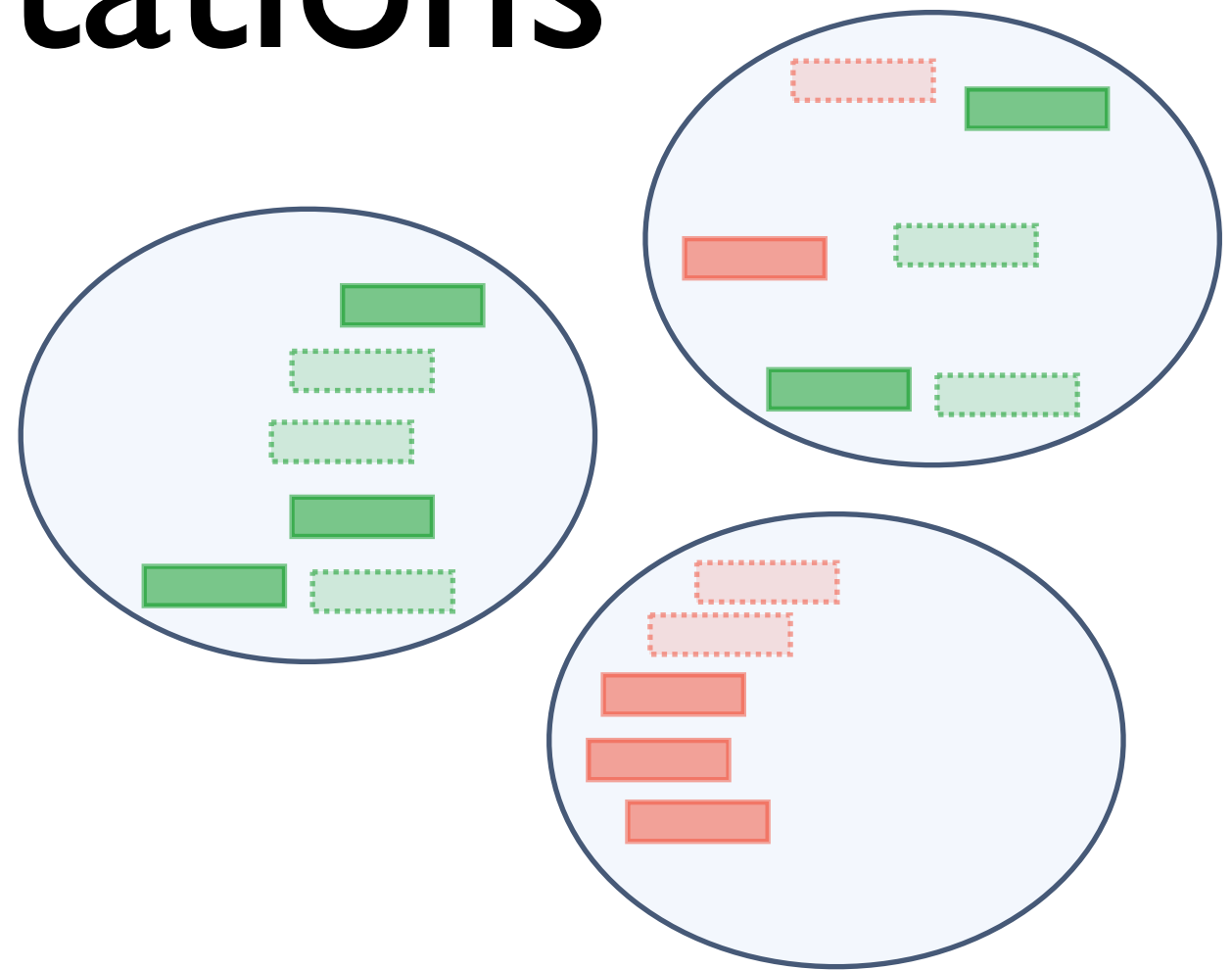


Parameter Estimation



$$p(\text{fact}) = \frac{\text{count}(\text{fact is true})}{\text{Number of interpretations}}$$

Learning from partial interpretations



- Not all facts observed
- Soft-EM
- use expected count instead of count
- $P(Q | E)$ -- conditional queries !

Learning from single facts / entailment



- Only true facts are given; e.g. as in HMM
 - key setting in PRISM, also in ProbLog
- EM-based, variations exist
- use **expected count** instead of **count**
- $P(Q | E)$ -- conditional queries !

Bayesian Parameter Learning

- Learning as inference (e.g., Church)
- Prior distributions for parameters
- Given data, find most likely parameter values

Information Extraction in NELL

Recently-Learned Facts [twitter](#) [Refresh](#)

instance	iteration	date learned	confidence
<u>kelly_andrews</u> is a <u>female</u>	826	29-mar-2014	98.7
<u>investment_next_year</u> is an <u>economic sector</u>	829	10-apr-2014	95.3
<u>shibenik</u> is a <u>geopolitical entity</u> that is an organization	829	10-apr-2014	97.2
<u>quality web design work</u> is a <u>character trait</u>	826	29-mar-2014	91.0
<u>mercedes benz cls by carlsson</u> is an <u>automobile manufacturer</u>	829	10-apr-2014	95.2
<u>social work</u> is an academic program <u>at the university rutgers university</u>	827	02-apr-2014	93.8
<u>dante wrote</u> the book <u>the divine comedy</u>	826	29-mar-2014	93.8
<u>willie aames</u> was <u>born in</u> the city <u>los angeles</u>	831	16-apr-2014	100.0
<u>kitt peak</u> is a mountain <u>in the state or province arizona</u>	831	16-apr-2014	96.9
<u>greenwich</u> is a park <u>in the city london</u>	831	16-apr-2014	100.0

↑
instances for many
different relations

↑
degree of certainty

Rule learning in NELL

- Original approach
 - Make probabilistic data deterministic
 - run classic rule-learner (variant of FOIL)
 - re-introduce probabilities on learned rules and predict

Probabilistic Rule Learning

- Learn the rules directly in a PLP setting
- Generalize relational learning and inductive logic programming directly towards probabilistic setting
- Traditional rule learning/ILP as a special case
- Apply to probabilistic databases like NELL
- Approach in PPR (Cohen et al) and in ProbLog (IJCAI-15)

NELL

Table 5: Number of facts per predicate (NELL athlete dataset)

athletecoach(person,person)	18	athleteplaysforteam(person,team)	721
athleteplayssport(person,sport)	1921	teamplaysinleague(team,league)	1085
athleteplaysinleague(person,league)	872	athletealsoknownas(person,name)	17
coachesinleague(person,league)	93	coachesteam(person,team)	132
teamhomestadium(team,stadium)	198	teamplayssport(team,sport)	359
athleteplayssportsteamposition(person,position)	255	athlethomestadium(person,stadium)	187
athlete(person)	1909	attraction(stadium)	2
coach(person)	624	female(person)	2
male(person)	7	hobby(sport)	5
organization(league)	1	person(person)	2
personafrika(person)	1	personasia(person)	4
personaaustralia(person)	22	personcanada(person)	1
personeurope(person)	1	personmexico(person)	108
personus(person)	6	sport(sport)	36
sportsleague(league)	18	sportsteam(team)	1330
sportsteamposition(position)	22	stadiumoreventvenue(stadium)	171

athleteplaysforteam

athleteplaysforteam(A,B) :- coachesteam(A,B).

0.875::athleteplaysforteam(A,B) :- teamhomestadium(B,C), athletehomestadium(A,C).

0.99080::athleteplaysforteam(A,B) :- teamhomestadium(B,_), male(A), athleteplayssport(A,_).

0.75::athleteplaysforteam(A,B) :- teamhomestadium(B,_), athleteplaysinleague(A,C), teamplaysinleague(B,C), athlete(A).

0.75::athleteplaysforteam(A,B) :- teamplayssport(B,C), athleteplayssport(A,C), coach(A), teamplaysinleague(B,_).

0.97555::athleteplaysforteam(A,B) :- personus(A), teamplayssport(B,_).

0.762::athleteplaysforteam(A,B) :- teamplayssport(B,C), athleteplayssport(A,C), personmexico(A), teamplaysinleague(B,_).

0.52571::athleteplaysforteam(A,B) :- teamplayssport(B,C), athleteplayssport(A,C), athleteplaysinleague(A,_), teamplaysinleague(B,_), athlete(A), teamplayssport(B,C).

0.50546::athleteplaysforteam(A,B) :- teamplayssport(B,_), teamplaysinleague(B,C), athleteplaysinleague(A,C), athleteplayssport(A,_).

0.50::athleteplaysforteam(A,B) :- teamplayssport(B,_), teamplaysinleague(B,C), athleteplaysinleague(A,C).

0.52941::athleteplaysforteam(A,B) :- teamplayssport(B,_), teamhomestadium(B,_), coach(A), teamplaysinleague(B,_).

0.55287::athleteplaysforteam(A,B) :- teamplayssport(B,_), teamplaysinleague(B,C), athleteplaysinleague(A,C), athlete(A).

0.46875::athleteplaysforteam(A,B) :- teamplayssport(B,_), teamplaysinleague(B,_), coach(A), teamhomestadium(B,_).

Part IV: Dynamics

Dynamics: Evolving Networks



- *Travian*: A massively multiplayer real-time strategy game
 - Commercial game run by TravianGames GmbH
 - ~3.000.000 players spread over different “worlds”
 - ~25.000 players in one world

[Thon et al., MLJ 11, ECML 08]



World Dynamics

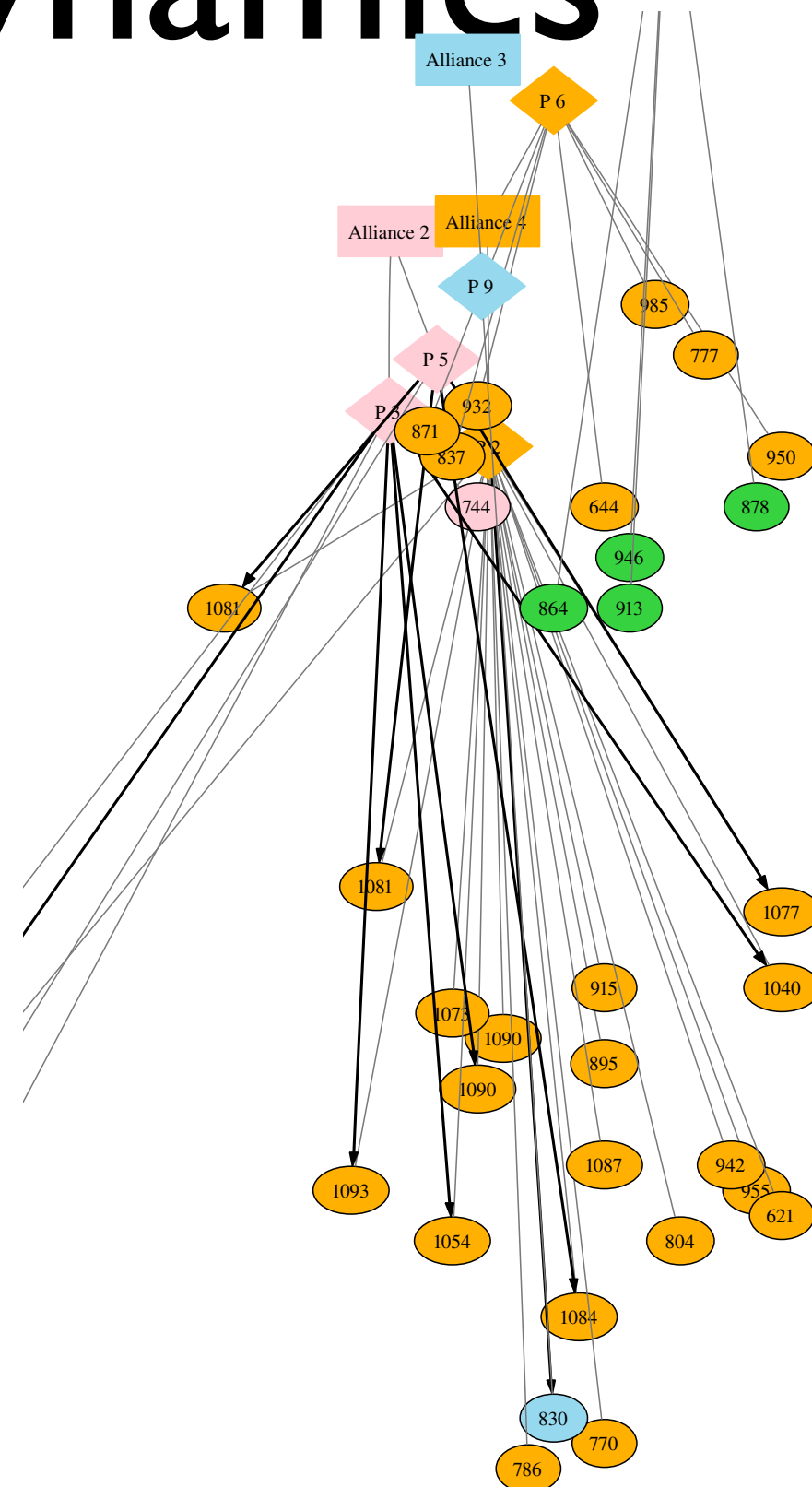
Fragment of world with

~10 alliances
~200 players
~600 cities

alliances color-coded

Can we build a model
of this world ?
Can we use it for playing
better ?

[Thon, Landwehr, De Raedt, ECML08]



World Dynamics

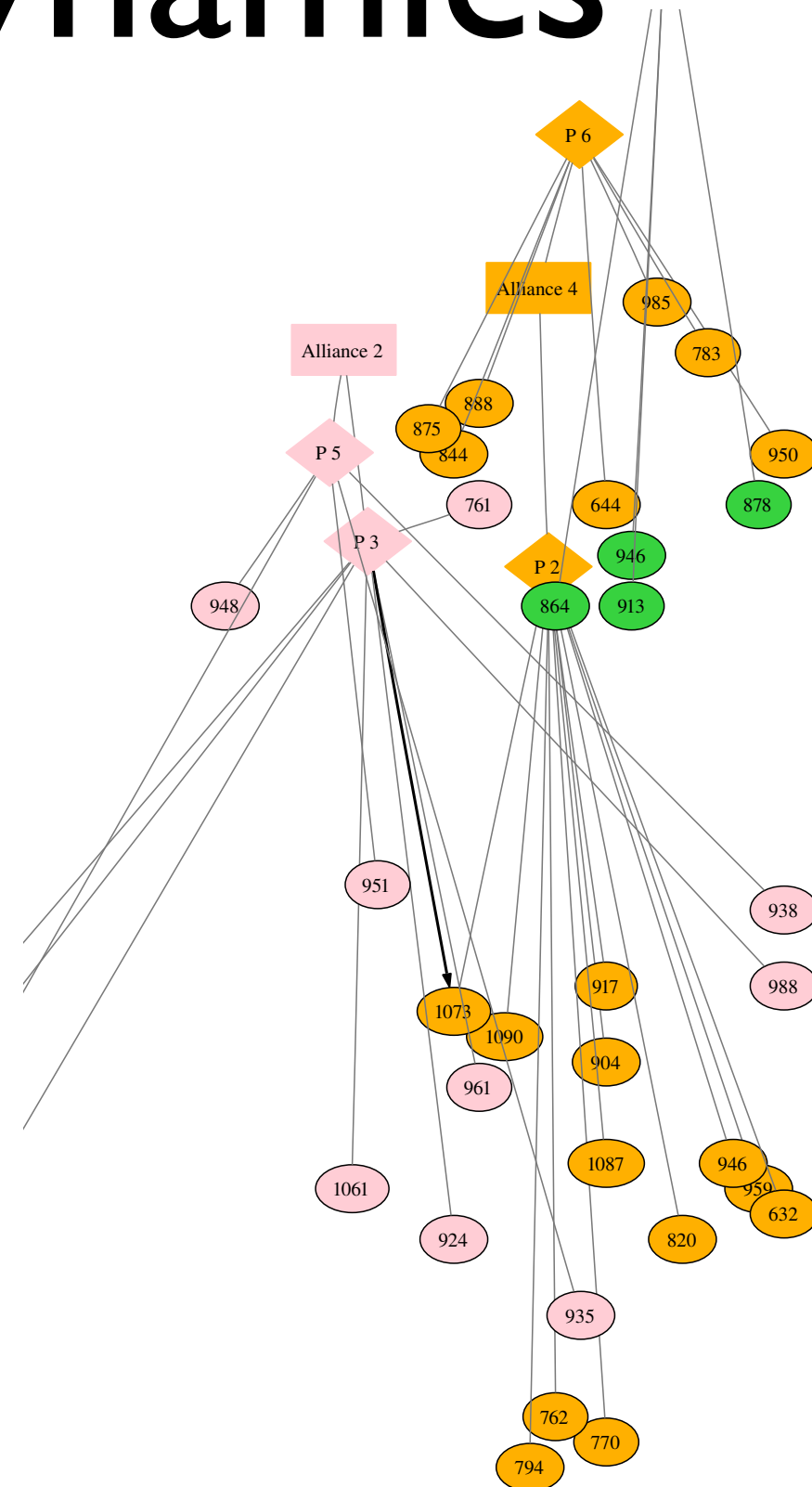
Fragment of world with

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~200 players
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alliances color-coded

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of this world ?
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[Thon, Landwehr, De Raedt, ECML08]



World Dynamics

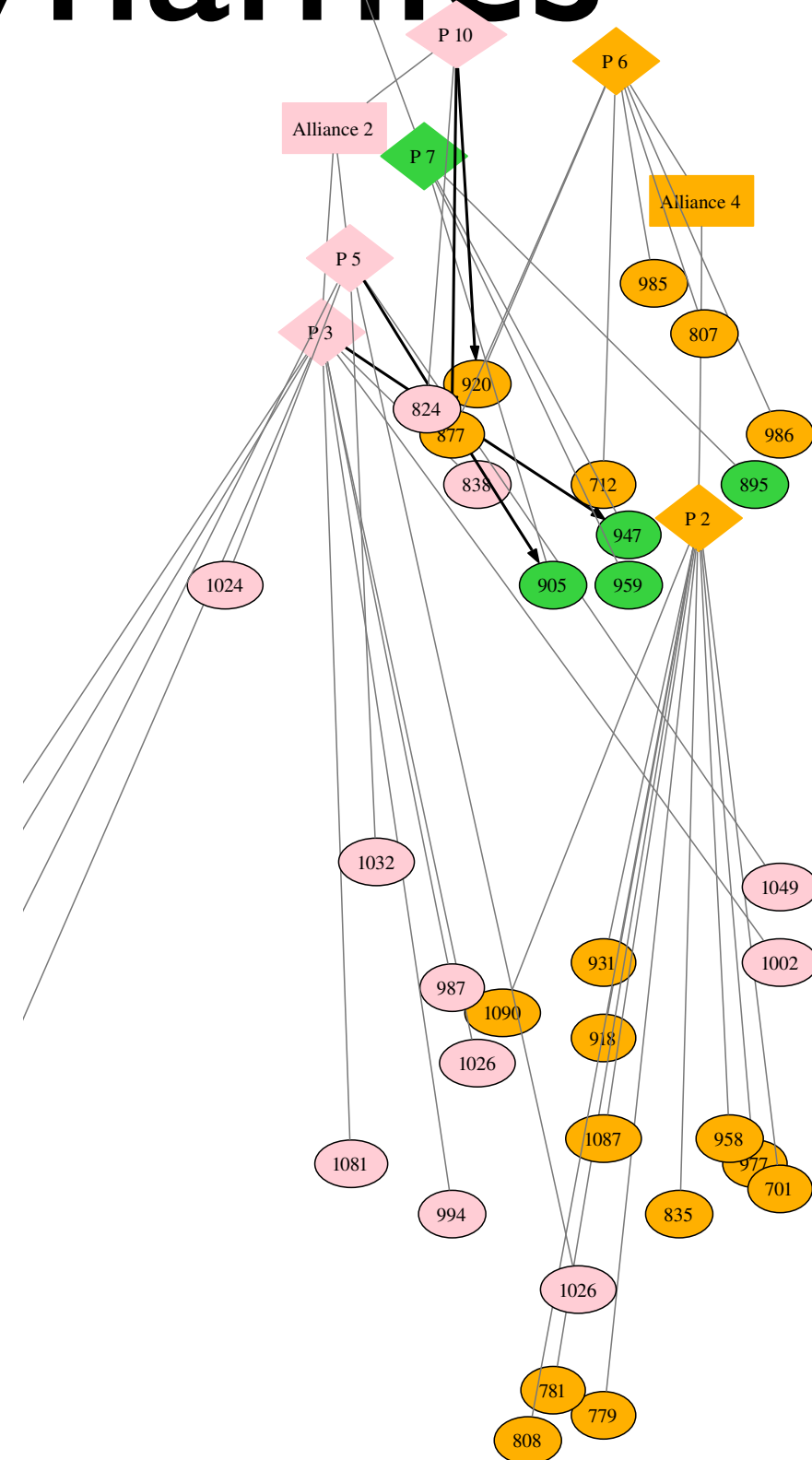
Fragment of world with

~10 alliances
~200 players
~600 cities

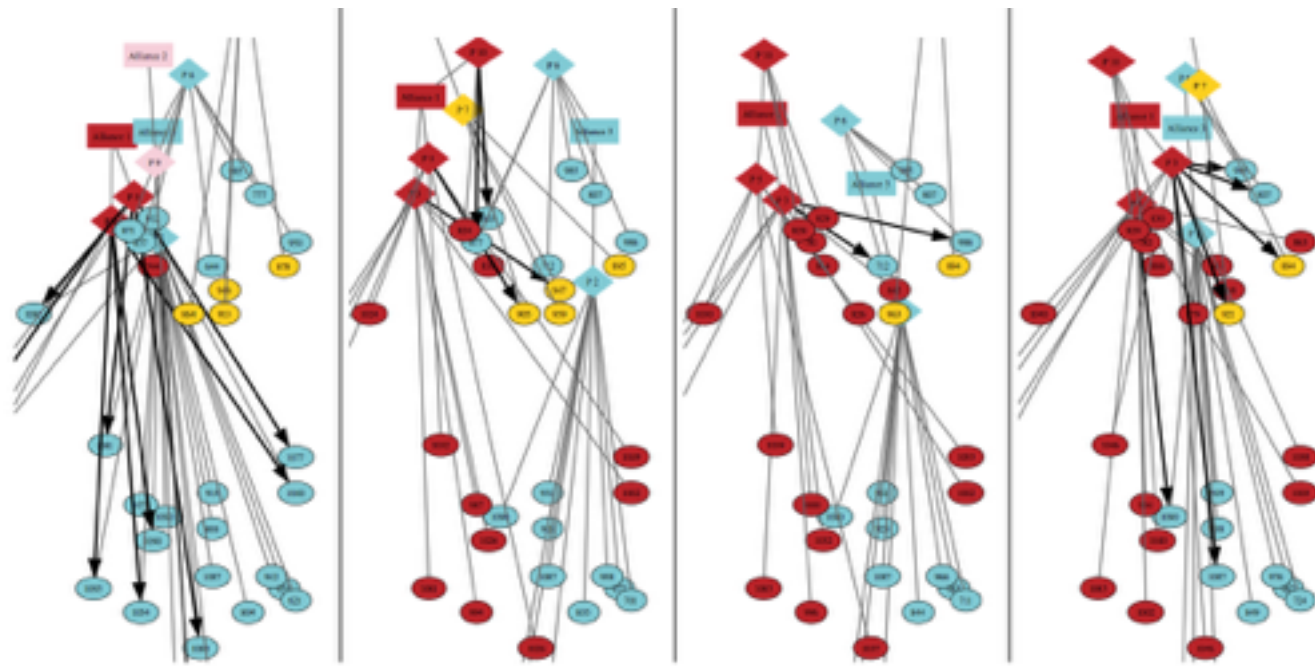
alliances color-coded

Can we build a model
of this world ?
Can we use it for playing
better ?

[Thon, Landwehr, De Raedt, ECML08]



Causal Probabilistic Time-Logic (CPT-L)



how does the world change over time?

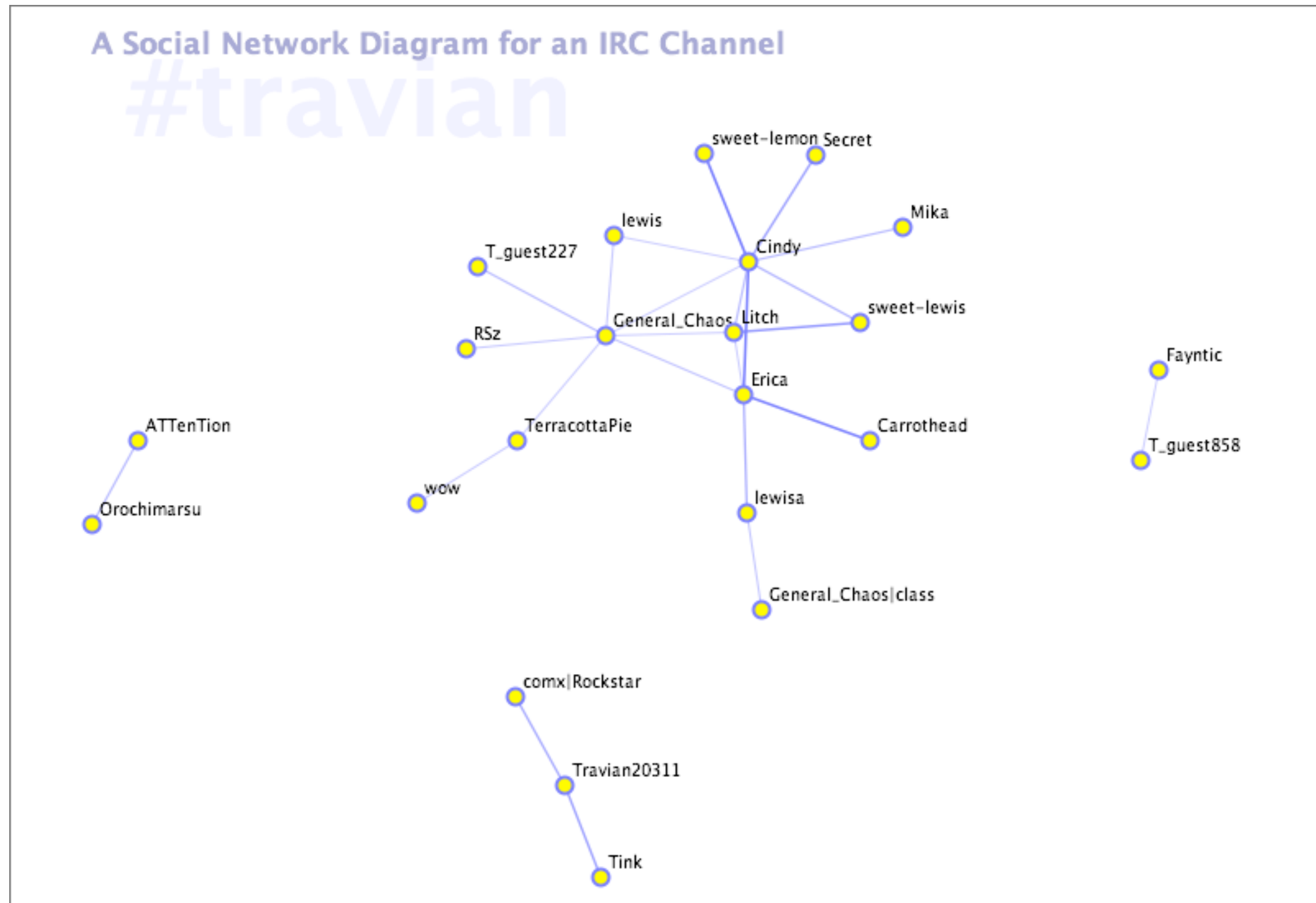
one of the **effects** holds at time $T+1$

```
0.4 :: conquest (Attacker, C) ; 0.6 :: nil <-
```

```
city (C, Owner) , city (C2, Attacker) , close (C, C2) .
```

if **cause** holds at time T

Social Network of Chats



Limitations CPT-L

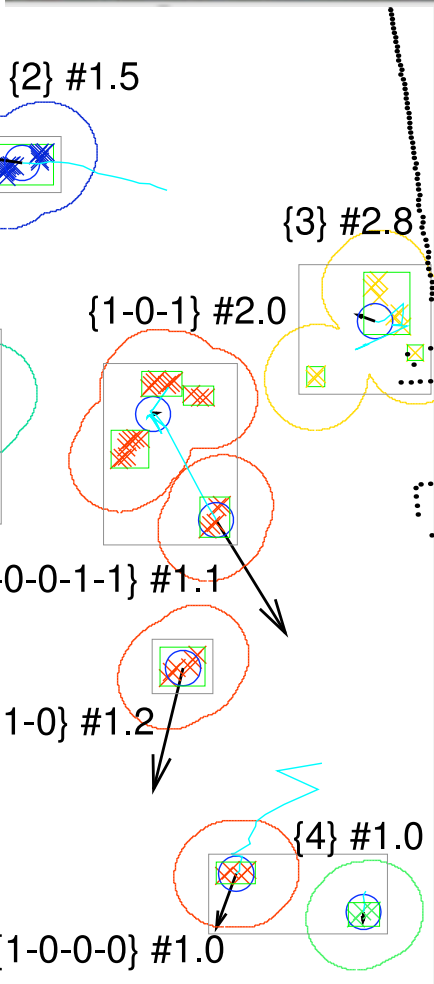
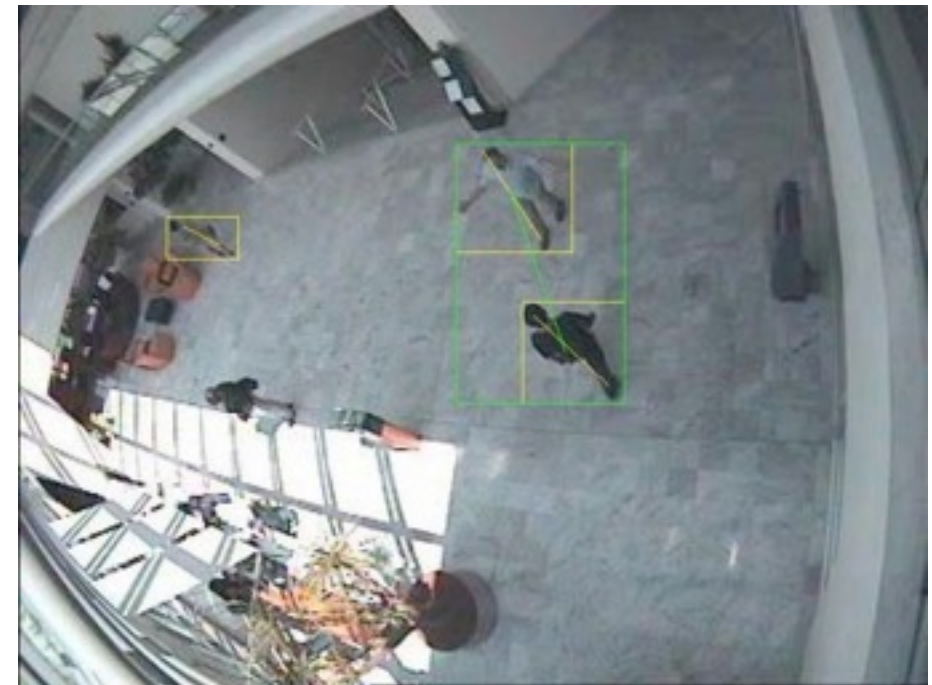
Inference slow / scalability

- uses knowledge compilation method
- compile formula for $P(I_{t+1} | I_{[0,t]})$
- exponential in number of time steps

No continuous distributions

- needed for robotics / relational tracking applications

Relational Tracking



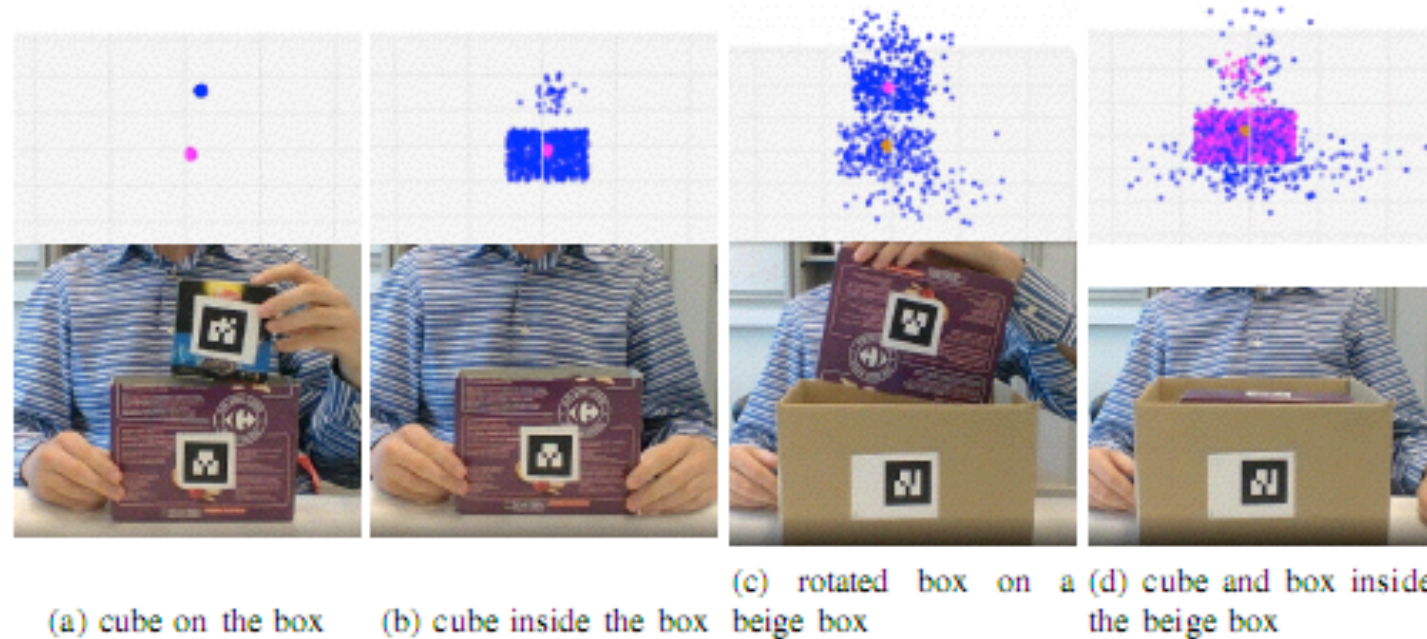
- Track people or objects over time? Even if temporarily hidden?
- Recognize activities?
- Infer object properties?



Relational State Estimation over Time

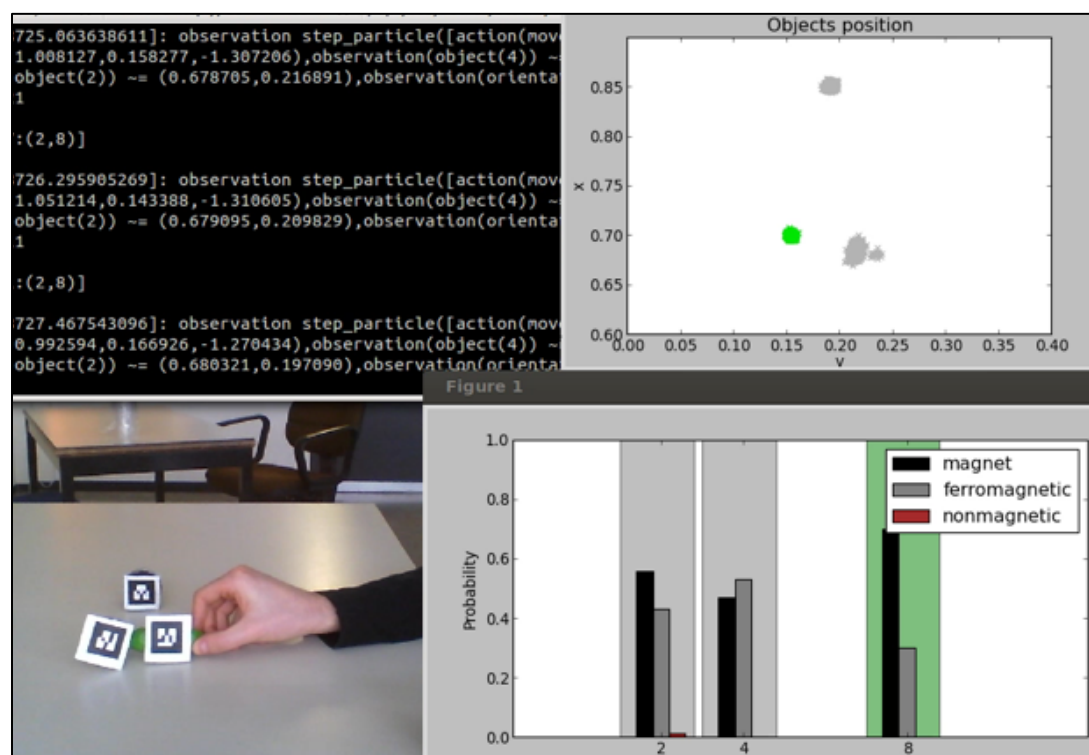
Magnetism scenario

- object tracking
- category estimation from interactions



Box scenario

- object tracking even when invisible
- estimate spatial relations

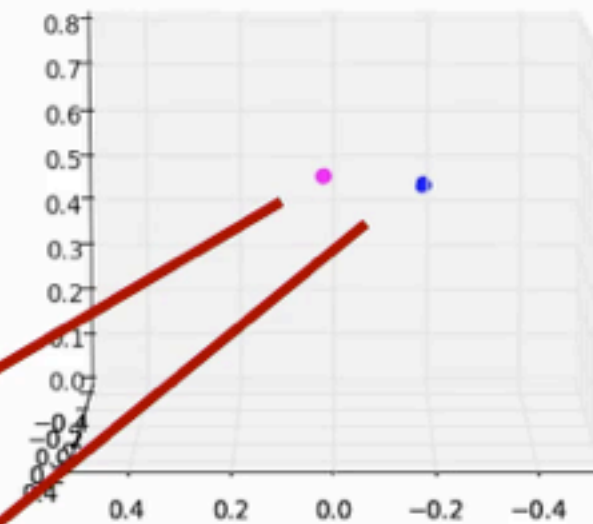


Speed 0x

Queries (updated every 5 steps)

```
[ ]  
on(X,Y):  
[1.0:(3,(table)),1.0:(4,(table))]  
inside(X,Y):  
[ ]  
tr_inside(X,Y):  
[ ]
```

Particles



Box ID=4

Cube ID=3

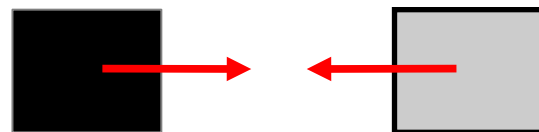
IROS 13

Magnetic scenario

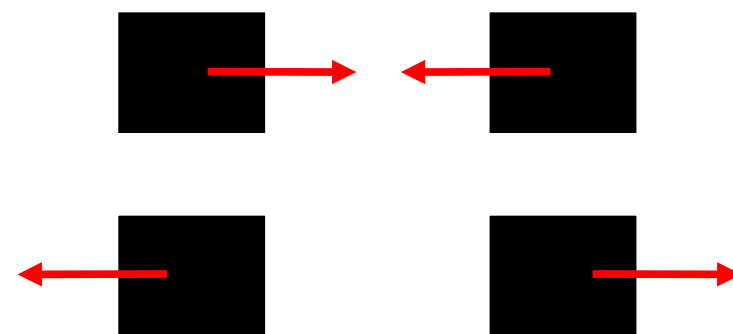
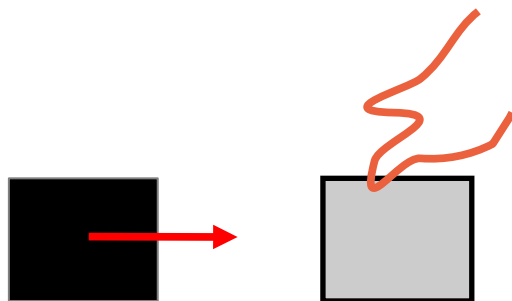
- 3 object types: magnetic, ferromagnetic, nonmagnetic

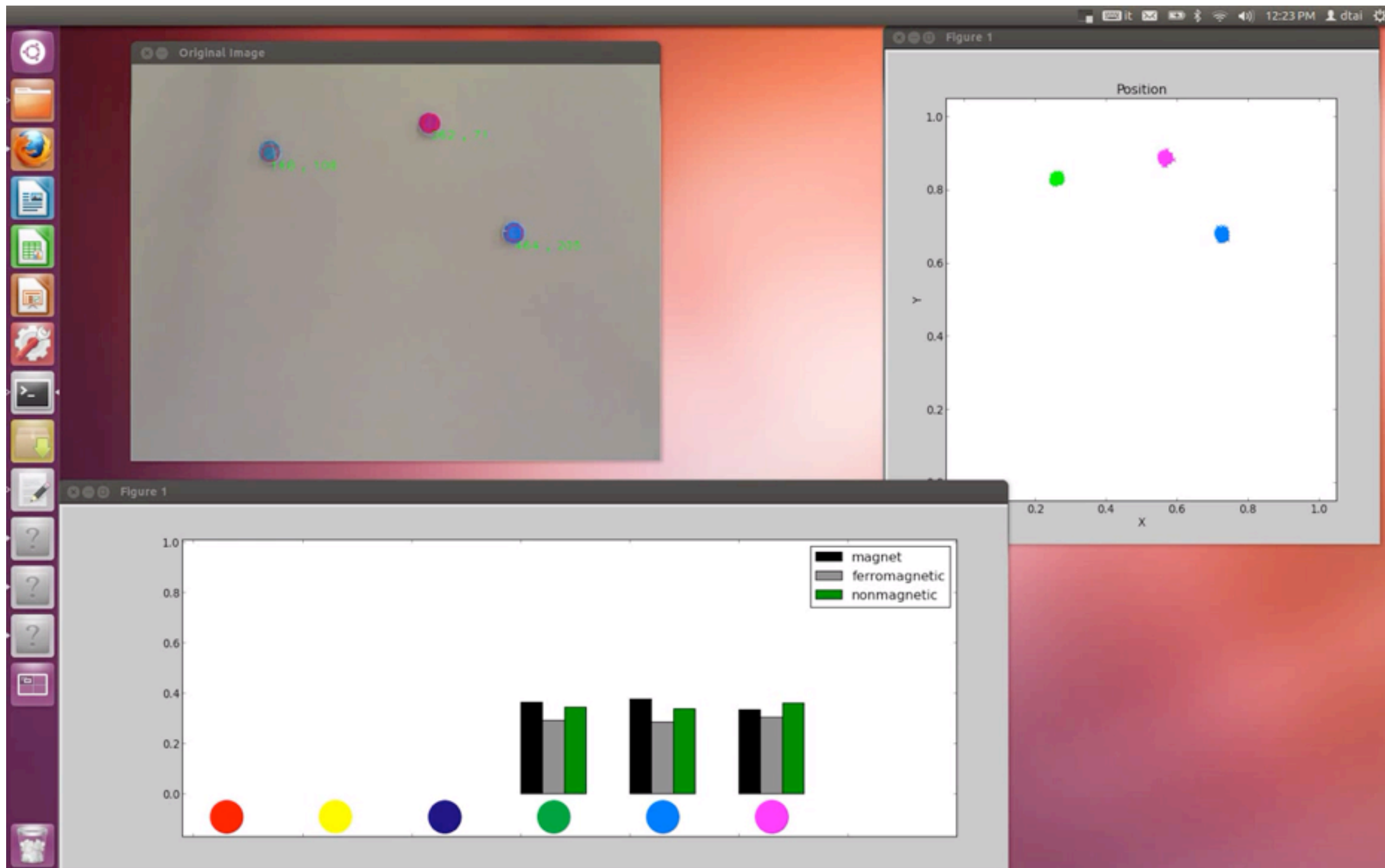


- Nonmagnetic objects do not interact
- A magnet and a ferromagnetic object attract each other

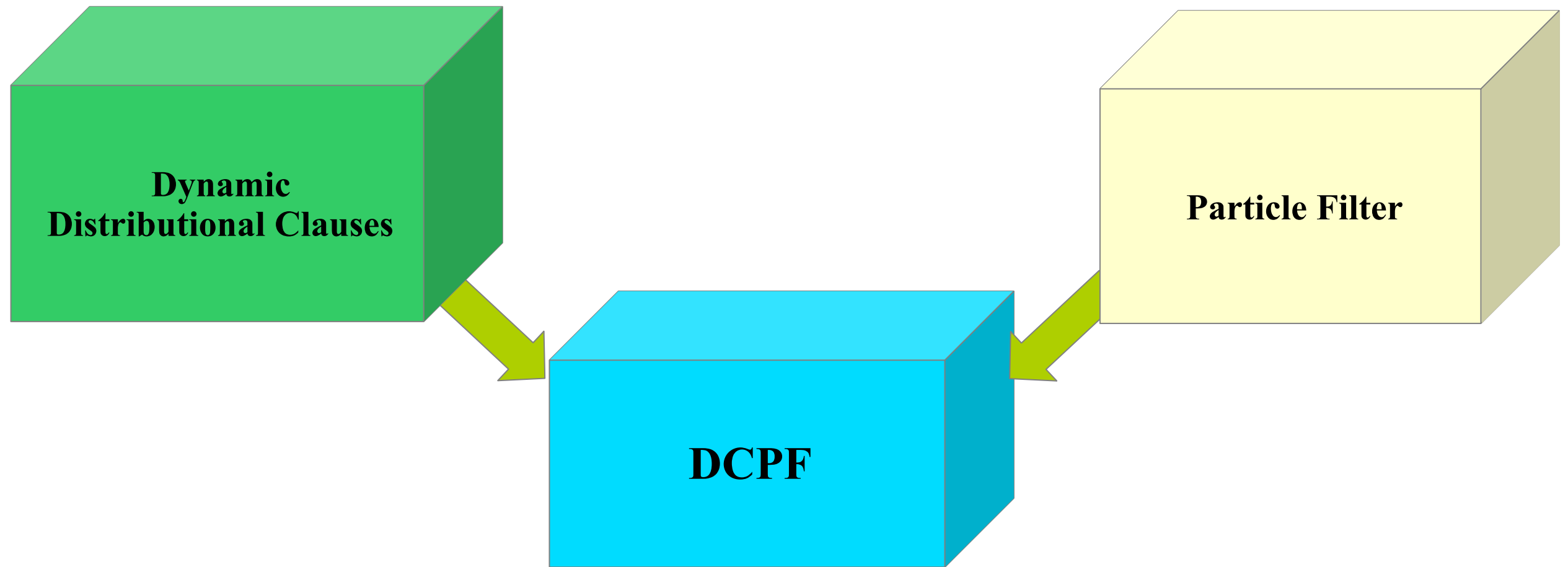


- Magnetic force that depends on the distance
- If an object is held magnetic force is compensated.





DC Particle Filter (DCPF)



Goal {

Flexible (relational) state representation

Fast inference (state estimation) in general models

“A particle filter for hybrid relational domains” IROS 2013

D. Nitti, T. De Laet, L. De Raedt

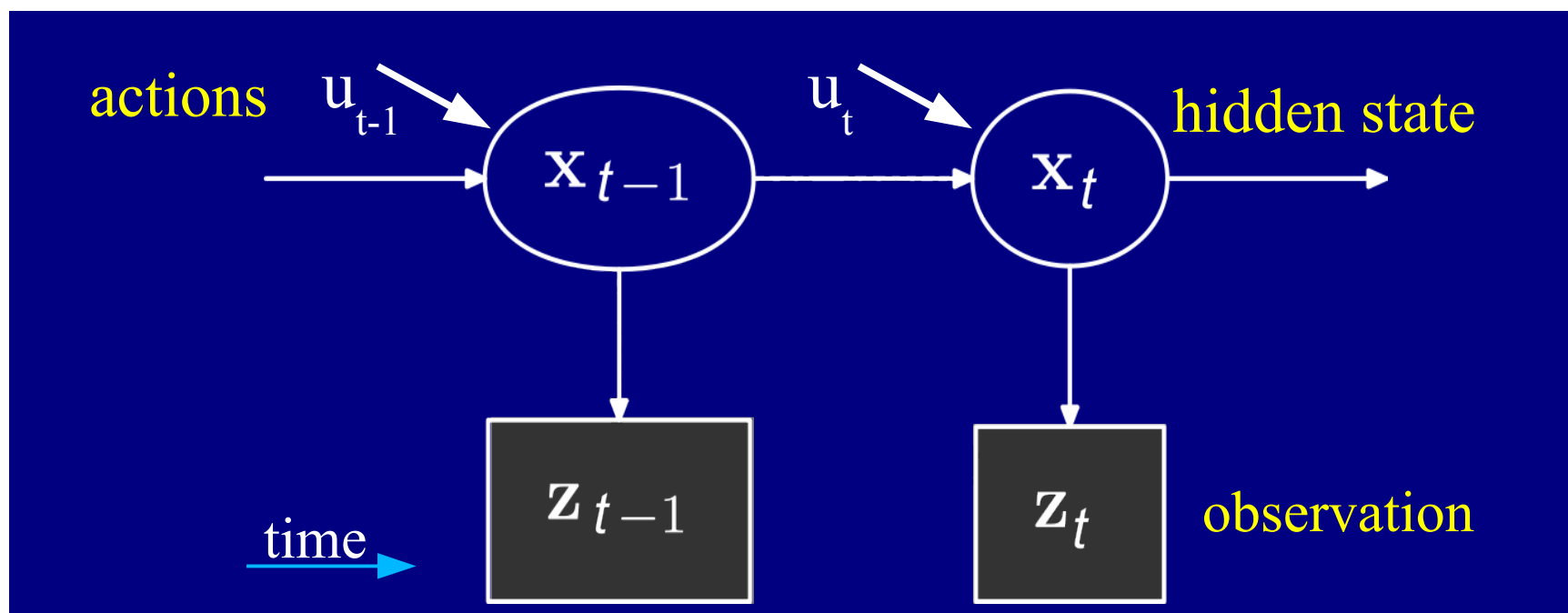
Dynamic Distributional Clauses

Prior distribution $p(x_0)$

State transition model $p(x_t|x_{t-1},u_t)$

Measurement model $p(z_t|x_t)$

Other rules: $p(x'_t|x''_t)$



Magnetic scenario

- 3 object types: magnetic, ferromagnetic, nonmagnetic

$\text{type}(X)_t \sim \text{finite}([1/3:\text{magnet}, 1/3:\text{ferromagnetic}, 1/3:\text{nonmagnetic}]) \leftarrow \text{object}(X).$

- 2 magnets attract or repulse

$\text{interaction}(A,B)_t \sim \text{finite}([0.5:\text{attraction}, 0.5:\text{repulsion}]) \leftarrow \text{object}(A), \text{object}(B), A < B, \text{type}(A)_t = \text{magnet}, \text{type}(B)_t = \text{magnet}.$

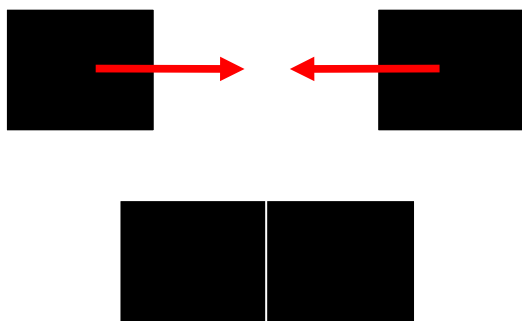
- Next position after attraction

$\text{pos}(A)_{t+1} \sim \text{gaussian}(\text{midpoint}(A,B)_t, \text{Cov}) \leftarrow$

$\text{near}(A,B)_t, \text{not}(\text{held}(A)), \text{not}(\text{held}(B)),$

$\text{interaction}(A,B)_t = \text{attr},$

$c/\text{dist}(A,B)_t^2 > \text{friction}(A)_t.$

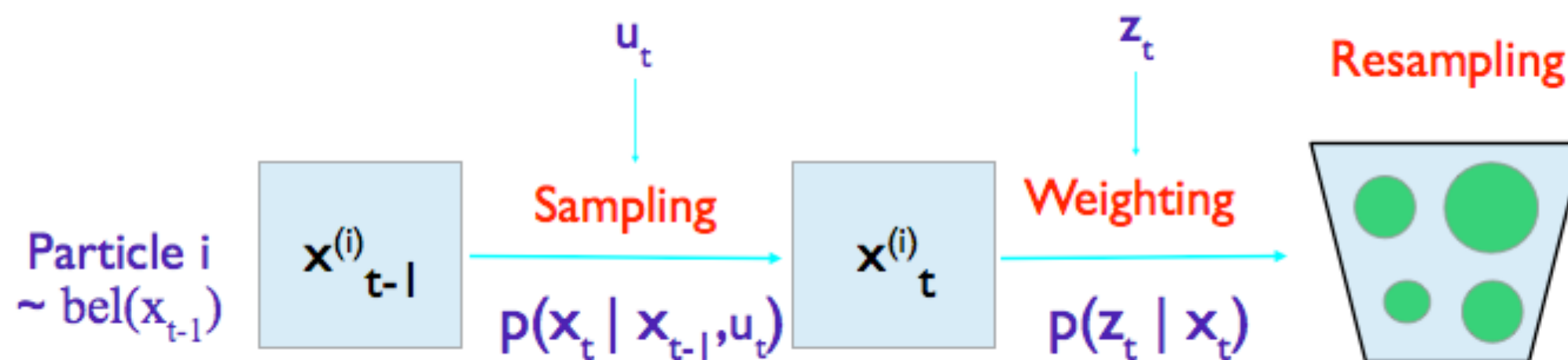


$\text{pos}(A)_{t+1} \sim \text{gaussian}(\text{pos}(A)_t, \text{Cov}) \leftarrow \text{not}(\text{attraction}(A,B)).$

Particle Filter

(Sequential Monte Carlo)

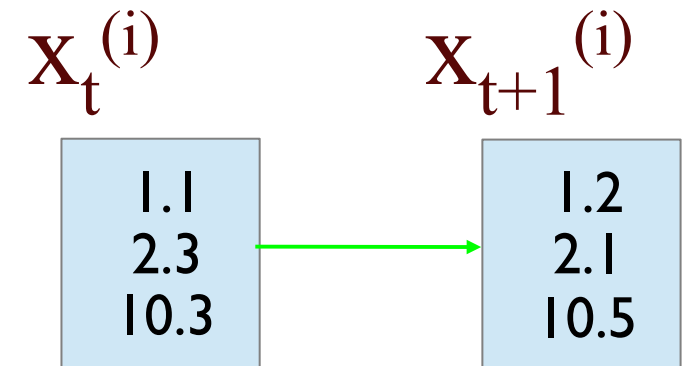
- Based on sampling \rightarrow approximate inference
- Particles (samples) to represent $\text{bel}(\mathbf{x}_t)$



Classical Particle Filter vs DCPF

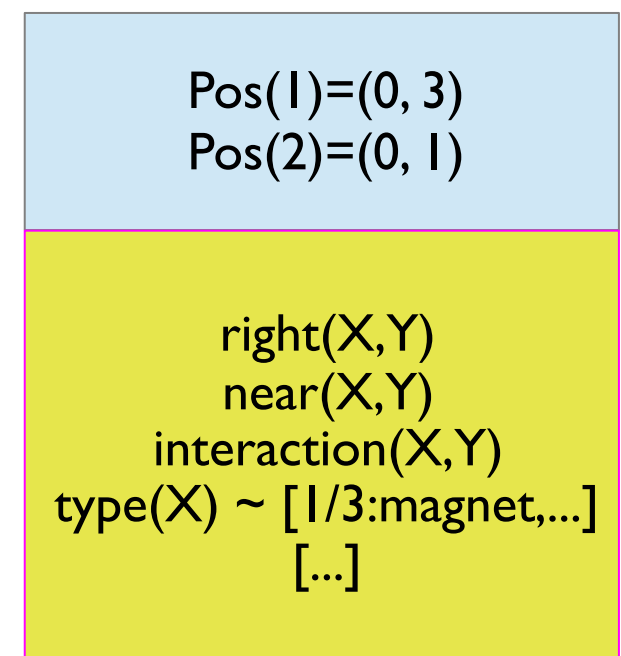
- Classical PF

- Fixed set of random variables
- Update the entire state



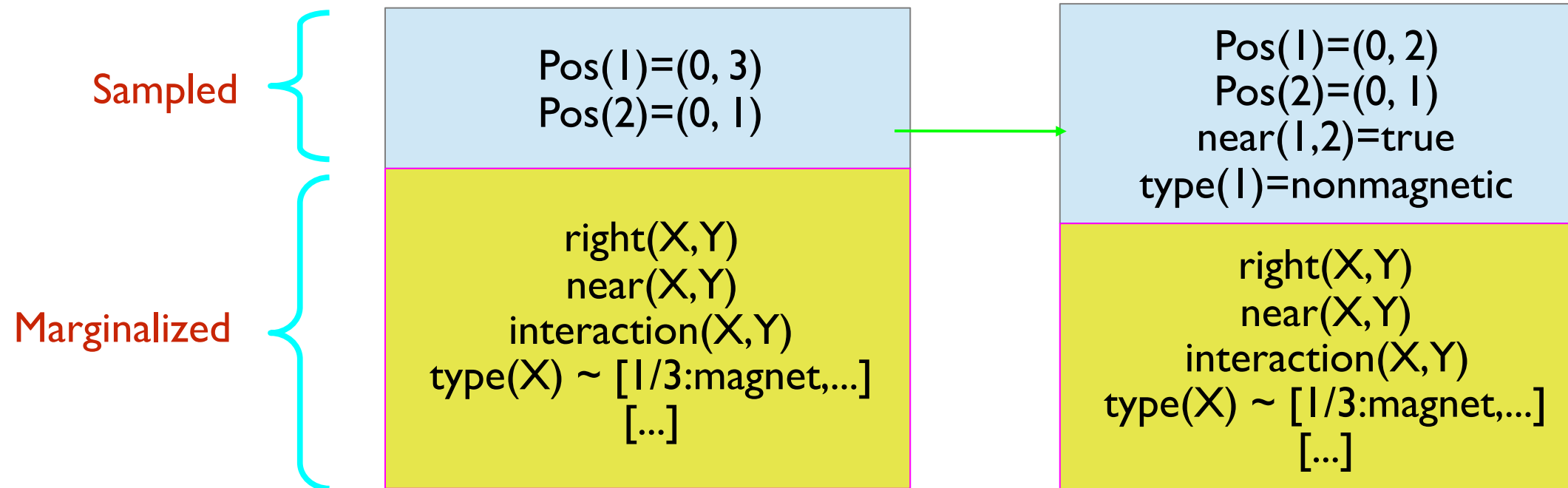
- DCPF

- **Adaptive state** (particle): the number of facts / random variables can change over time
- Particles are partial interpretations
- Expressive language

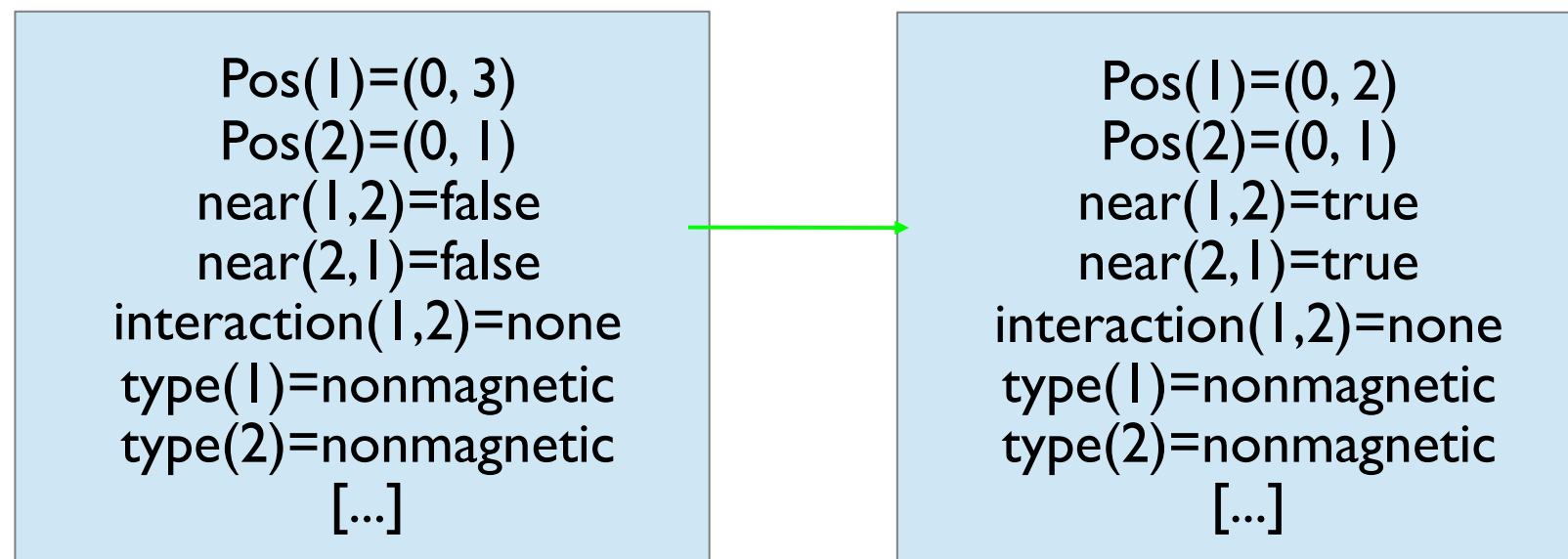


Optimized inference: partial state

Distributional Clauses Particle Filter (DCPF)



Classical particle filter



Inference in DCPF

Two steps:

Query $p(z_{t+1} | x_{t+1})$ (weighting + part of sampling step)

Query $p(x_{t+1} | x_t, u_{t+1})$ (to complete the sampling step)
using the DC inference

particles are partial interpretations

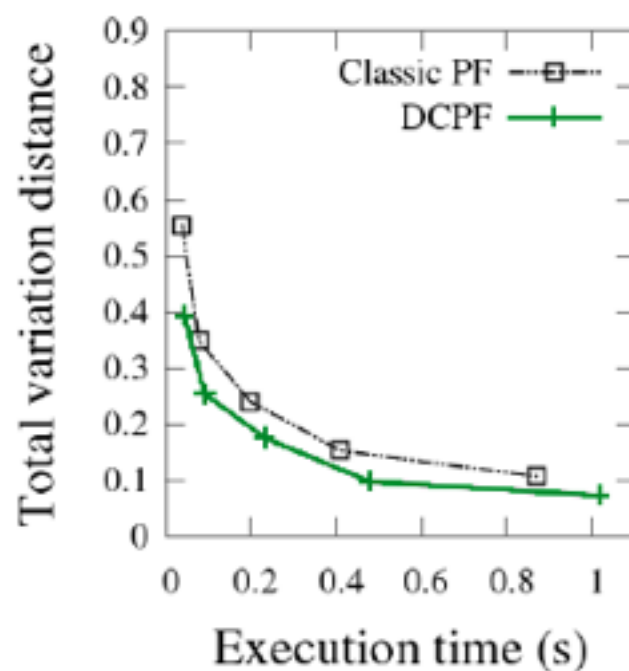
$\text{bel}(x_t)$ fully represented by $\{x_t^{(i)}\} \cup \text{Program}$

History $\{x_{0:t-1}^{(i)}\}$ not necessary

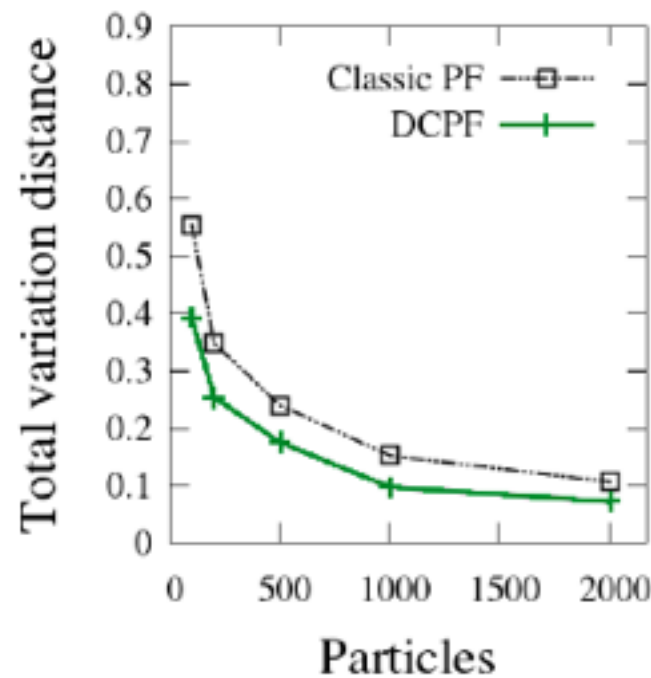
Issue: particles (interpretations) may grow till becoming complete

Experiments

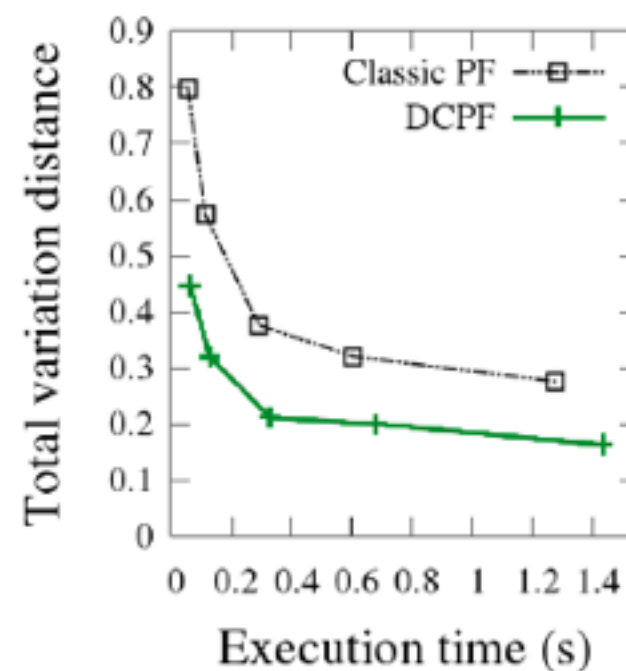
- Particles are partial state, remaining variables are marginalized
- Better performance in bigger models



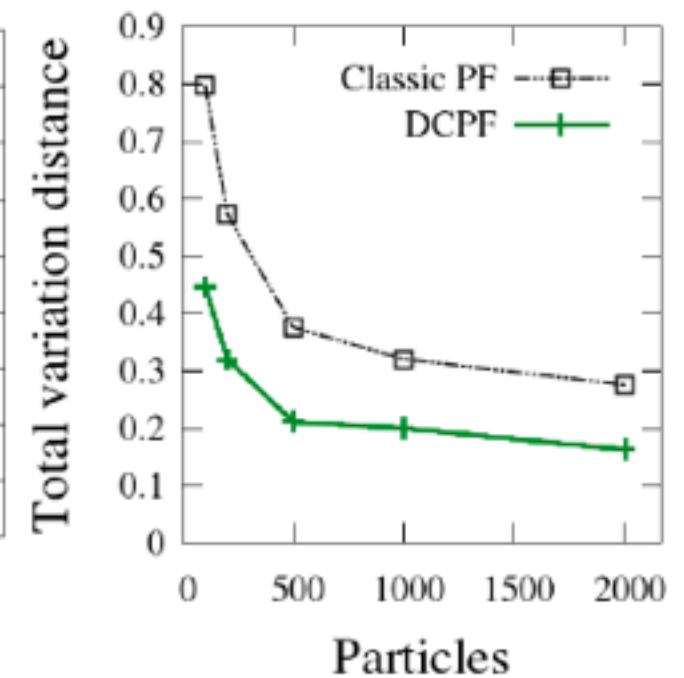
(a) 3 objects



(b) 3 objects



(c) 4 objects



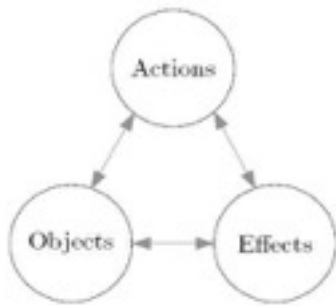
(d) 4 objects

Ongoing Work

- Online parameter learning [Nitti, ICRA 2014]
- Integrate with planning [Nitti, ECML 15, EWRL 15]
- Applications in robotics (also to learn affordances)

Learning relational affordances

Learn probabilistic model

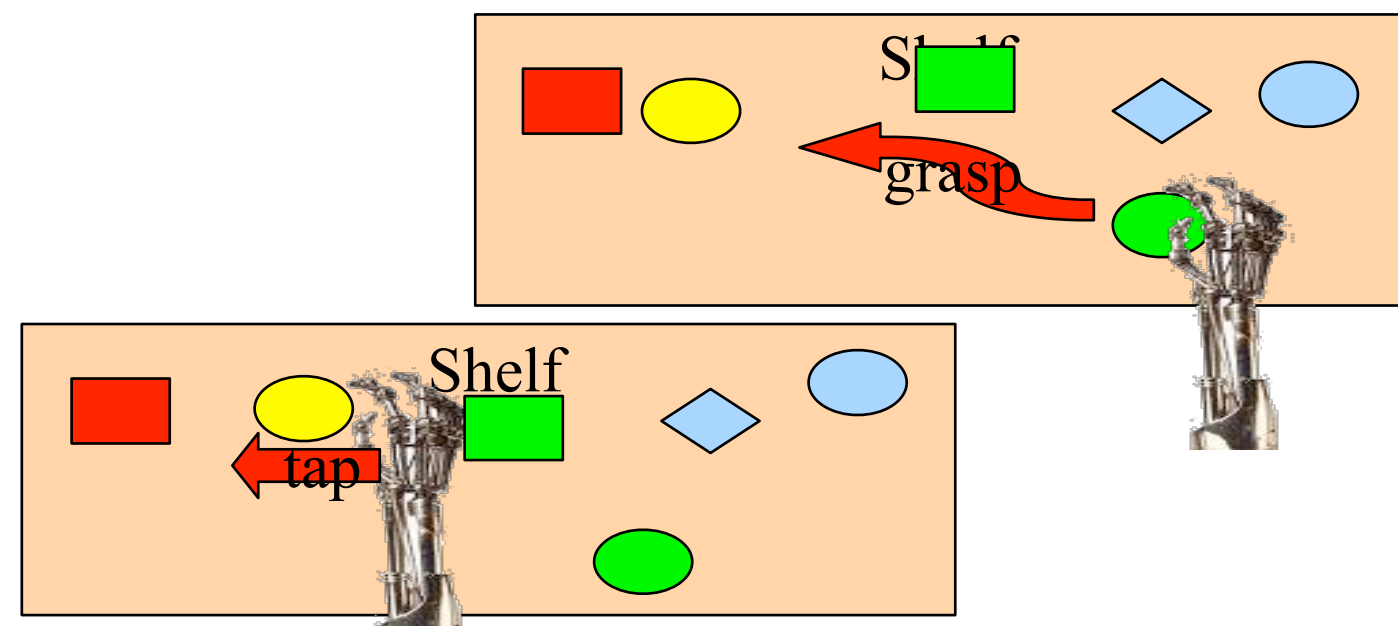
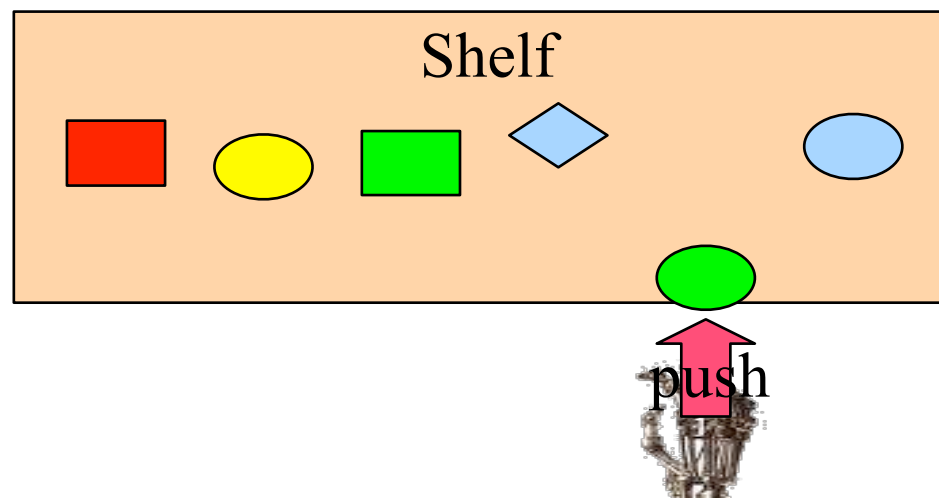


Inputs	Outputs	Function
(O, A)	E	Effect prediction
(O, E)	A	Action recognition/planning
(A, E)	O	Object recognition/selection

Learning relational
affordances
between
two objects
(learnt by experience)

From two object interactions
Generalize to N

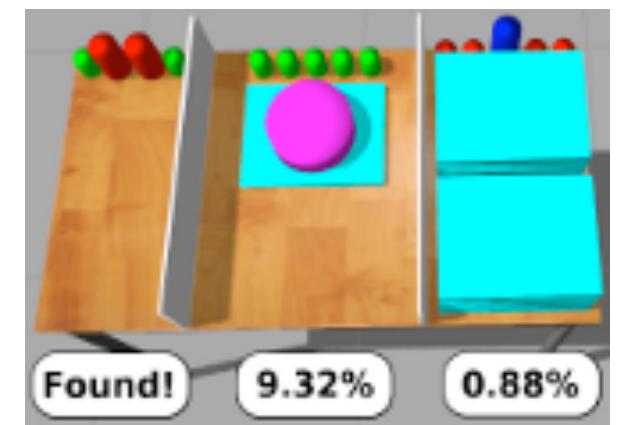
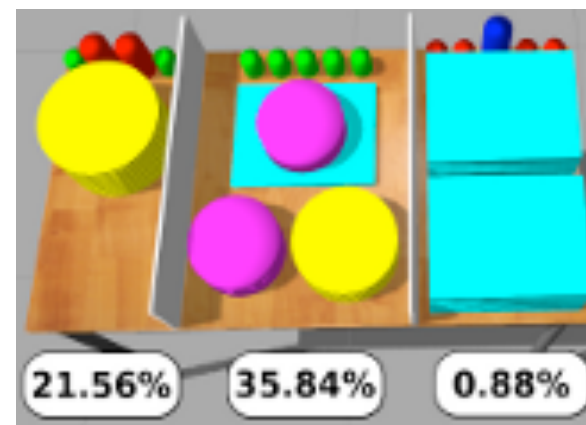
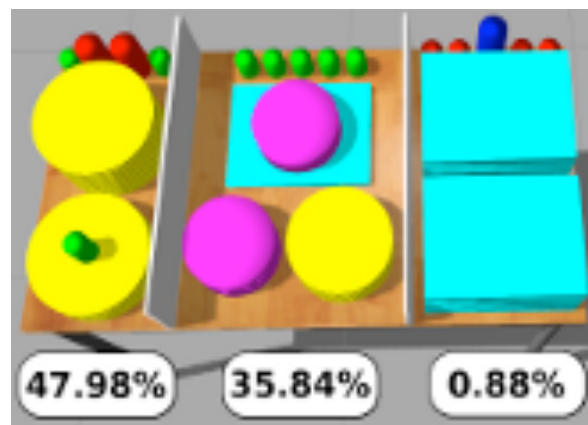
Moldovan et al. ICRA 12, 13, 14



Occluded Object Search



- Models of objects and their spatial arrangement
- different types of objects suitable for different tasks
- shelves with objects of different shape and size
- given a task, find an object to perform that task



ProbLog for activity recognition from video



CAVIAR-INRIA human
activity dataset

28 videos
 ≈ 26.500 frames

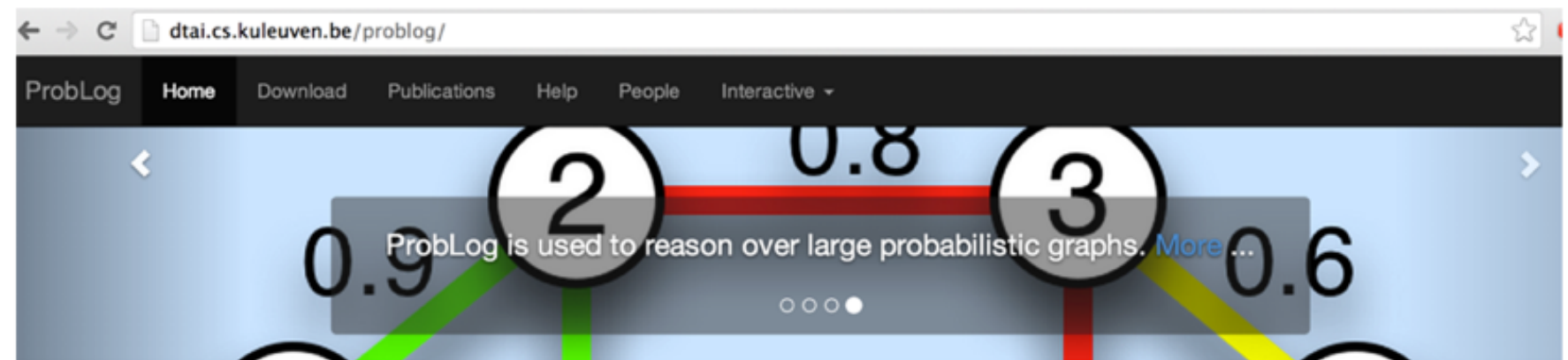
- Separation between low-level events (LLE) and high-level events (HLE)
 - LLE: *walking, running, active, inactive, abrupt*
 - HLE: *meeting, moving, fighting, leaving_object*
- Probabilistic Logic approach: *Event Calculus in ProbLog* (Prob-EC) to infer the high-level events from an **algebra** of low-level events.
- Example:

$$\begin{aligned} \text{initiatedAt}(\text{fighting}(P_1, P_2) = \text{true}, T) \leftarrow \\ \text{happensAt}(\text{abrupt}(P_1), T), \\ \text{holdsAt}(\text{close}(P_1, P_2, 44) = \text{true}, T), \\ \text{not happensAt}(\text{inactive}(P_2), T). \end{aligned}$$

Vaishak Belle
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Bart Demoen
Anton Dries
Daan Fierens
Jason Filippou
Bernd Gutmann
Manfred Jaeger
Gerda Janssens
Kristian Kersting
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Theofrastos Mantadelis
Wannes Meert
Bogdan Moldovan
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Joris Renkens
Kate Revoredo
Ricardo Rocha
Vitor Santos Costa
Dimitar Shterionov
Ingo Thon
Hannu Toivonen
Guy Van den Broeck
Mathias Verbeke
Jonas Vlasselaer

Thanks !

<http://dtai.cs.kuleuven.be/problog>



Introduction.

Probabilistic logic programs are logic programs in which some of the facts are annotated with probabilities.

ProbLog is a tool that allows you to intuitively build programs that do not only encode **complex interactions** between a large sets of **heterogenous components** but also the inherent **uncertainties** that are present in real-life situations.

The engine tackles several tasks such as computing the marginals given evidence and learning from (partial) interpretations. ProbLog is a suite of efficient algorithms for various inference tasks. It is based on a conversion of the program and the queries and evidence to a weighted Boolean formula. This allows us to reduce the inference tasks to well-studied tasks such as weighted model counting, which can be solved using state-of-the-art methods known from the graphical model and knowledge compilation literature.

The Language. Probabilistic Logic Programming.

ProbLog makes it easy to express complex, probabilistic models.

```
0.3::stress(X) :- person(X).  
0.2::influences(X,Y) :- person(X), person(Y).
```


PLP Systems

- **PRISM** <http://sato-www.cs.titech.ac.jp/prism/>
- **ProbLog2** <http://dtai.cs.kuleuven.be/problog/>
- **Yap Prolog** <http://www.dcc.fc.up.pt/~vsc/Yap/> includes
 - **ProbLogI**
 - **cplint** <https://sites.google.com/a/unife.it/ml/cplint>
 - **CLP(BN)**
 - **LP2**
- **PITA in XSB Prolog** <http://xsb.sourceforge.net/>
- **AILog2** <http://artint.info/code/ailog/ailog2.html>
- **SLPs** <http://stoics.org.uk/~nicos/sware/pepl>
- **contdist** <http://www.cs.sunysb.edu/~cram/contdist/>
- **DC** <https://code.google.com/p/distributional-clauses>
- **WFOMC** <http://dtai.cs.kuleuven.be/ml/systems/wfomc>

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